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Investigating the Relationship between Customer Wait Time and Operational Availability through Simulation Modeling

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December 2012

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INVESTIGATING THE RELATIONSHIP BETWEEN CUSTOMER WAIT TIME AND OPERATIONAL AVAILABILITY THROUGH SIMULATION MODELING

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ABSTRACT

Customer Wait Time (CWT) measures all supply chain processes, from the time a customer places an order until the item is delivered. The Marine Corps intermediate supply activity, the Supply Management Unit (SMU), has the primary task of reducing the amount of time it takes for the operating forces to receive supplies by stocking items close to the warfighter. Such forward positioning of repair parts shields the operating forces from delays found at the wholesale inventory level, thereby increasing the material readiness of the operating forces. Intuitively, decreasing CWT increases operational availability (A_o), but the degree and magnitude of this relationship has yet to be quantified. This lack of understanding pertaining to the relationship between A_o and CWT has led to arbitrary stock policies that do not account for the cost and benefit they provide. This project centers on monetizing the relationship between these variables through simulation modeling, and provides a tool whereby stock determination can be made based on desired end states.

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LIST OF ACRONYMS AND ABBREVIATIONS

A_o	Operational Availability
AAV	Amphibious Assault Vehicle
ADT	Administrative Delay Time
ASL	Authorized stocking list
ATLASS	Asset Tracking and Logistics and Supply System
BCT	Brigade Combat Team
CEC	Combat Essentiality Codes
CMC	Commandant of the Marine Corps
CWT	Customer Wait Time
DAAS	Defense Automated Addressing System
DAASC	Defense Automated Addressing System Center
DRRS-MC	Defense Readiness Reporting System-Marine Corps
EDA	Equipment Downtime Analyzer
EDCBM	Enhanced Dollar Cost Banding Model
EOQ	Economic Order Quantity
ERO	Equipment Repair Order
EROSL	Equipment Repair Order Shopping List
FMC	Fully Mission Capable
GCSS-MC	Global Combat Support System-Marine Corps
CIVaR	Conditional Inventory Value-at-Risk
LCMI	Life Cycle Modeling Integrator
LM-2	Logistics Management 2nd Generation
LPCWT	Last Part CWT
LTI	Limited Technical Inspection
MARES	Marine Corps Automated Readiness Evaluation System
MDT	Maintenance Downtime
MEF	Marine Expeditionary Force
MERIT	Marine Corps Equipment Readiness Information Tool

MILSTRIP	Military Standard Requisitioning & Issue Procedures
MIMMS	Marine Corps Integrated Maintenance Management System
MTBF	Mean Time between Failure
MTTR	Mean Time to Repair
NAVSUP	Navy Supply Systems Command
NICP	National Inventory Control Points
NMC	Non-Mission Capable
NMCM	Non-Mission Capable Maintenance
NMCS	Non-Mission Capable Supply
NSN	National Stock Number
PEI	Principal End Item
RCT	Repair Cycle Time
SASSY	Supported Activities Supply System
SECREP	Secondary Repairable
SOE	System Operational Effectiveness
SOS	Source of supply
SMRC	Source, Maintenance, and Recoverability Codes
SMU	Supply Management Unit
SSA	Supply Support Activities
StDev	Standard Deviation
TACOM	U.S. Army Tank-automotive and Armaments Command
TAMCN	Table of Authorized Material Control Number
USD AT&L	Under-Secretary of Defense for Acquisition, Technology, and Logistics
U/I	Unit of Issue

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I. INTRODUCTION

According to the U.S. Government Accountability Office (2011), the total spending on logistics by the Department of Defense in 2010 amounted to over $210 billion. The GAO website acknowledges that supply chain management has been, and continues to be, one of the Department of Defense's (DoD) "key weaknesses" (GAO, 2012) every year dating back to 1990. The latest report by the GAO came out in July of 2011, and it provides that the DoD "does not have the performance measures that assess the overall effectiveness and efficiency of the supply chain across the enterprise" (GAO, 2011). Because Supply Chain Management is listed as a key weakness for DoD, their supply chain management practices have been placed on a watch list and Congress has charged DoD with correcting this problem. DoD's latest response is the *2010 Logistics Strategic Plan* (GAO, 2011).

The *Logistics Strategic Plan* seeks to find areas to reduce DoD's excess inventories. The DoD solution to reduction of inventory, however, is not aimed at across the board cuts, but instead finding inventory efficiencies through the improvement of requisition tracking and information. These are enterprise solutions that pertain beyond any one service. Adding asset visibility and real time requisition capabilities can reduce such factors as customer wait time (CWT), which correspondingly will reduce maintenance down time (MDT). Asset visibility aids DoD in knowing how much inventory it has on hand and in the transportation pipeline at any one time. As demand data, asset visibility, and CWT information is refined, DoD is in a better position to predict its required inventory per period of time. The first step to achieving these types of inventory reductions is the implementation of the right measures of effectiveness.

On December 14, 2000, the USD AT&L released DoD Instruction 4140.61 entitled *Customer Wait Time and Time Definite Delivery* that directed all services to implement the use of CWT to measure the responsiveness of their systems. The instruction defined CWT as "a measurement of the total elapsed time between the issuance of a customer order and satisfaction of that order" (DoD Instruction, 2000, p. 2). This directive was all encompassing, and charged each service with taking the necessary

steps to fully implement and report the use of CWT as a performance measure (DoD Instruction, 2000). CWT allows for the computation of lead-time and serves to aid DoD agencies in establishing accurate levels of safety stock to satisfy demand. The relationship between CWT and operational availability (A_o) is the focus of this study.

There are three potential benefits to using CWT to measure performance. First, CWT can be used to determine lead-time in the Economic Order Quantity (EOQ) and other common inventory stocking methodologies. Secondly, CWT can be used to measure effectiveness of the supply chain. Through the effective implementation of CWT, DoD can show whether or not supply support agencies are meeting their customer service goals. Lastly, the relationship between A_o and CWT can show how forward positioned inventories lend to reductions in the equipment down time and improved equipment readiness. According to Girardini, Lackey, and Peltz (2007), the key to high equipment readiness is the proper stocking methodologies of Supply Support Activities.

The Supply Support Activity for the Marine Corps is Supply Management Unit (SMU). The SMU is an intermediate retail activity that is responsible for sustaining a Marine Expeditionary Force (MEF) for 60 days while in a forward deployed environment. The SMU's tasks include "requirements determination, stock replenishment, issue and redistribution actions, inquiry response, and excess/disposal determination" (USMC, 1984). In the continental United States (CONUS), this responsibility remains unchanged, and the SMU focuses on sustaining training and operations of units and at home station as well as abroad.

Although each SMU activity independently supports operations of its respective MEF, CWT metrics in the Marine Corps are aggregated by Marine Corps Logistics Command (MarCorLogCom), in Albany, Georgia instead of being tracked at each of the intermediate supply activity level (IG, 2007). This poses problems in identifying the effectiveness of each SMU, and developing best practices. The Marine Corps has intermediate supply activities at each of the MEFs and it is the measurement of each SMU's performance that matters most.

A. THE PROBLEM

Certain critical repair parts are consistently shown to have longer customer wait times, and are common contributors long periods of delay when equipment is not mission capable, or *deadlined*. The intuitive understanding that a decrease in CWT will have a positive effect on A_o can be quantified through the mathematical formula for A_o which shows that CWT is one of several factors that determine A_o. However, turning this intuition into a precise, actionable quantification involves a detailed study of the relationship between CWT and A_o over time, because CWT and the other factors that determine A_o are stochastic, and may not have a stable distribution over time (they may not be *stationary)*. Since the factors determining A_o are stochastic, then although an investment in CWT may *on average* have a given effect on A_o the return on that investment will itself be stochastic as well. In addition, since the factors may not be stationary, then an investment made in reducing CWT in 2012 based on 2011 data may not have the predicted effect in 2013.

Hence, the precise actionable relationship between CWT is an empirical question that cannot be simply quantified by examining the average values of the factors involved and resorting to the formula. The quantification instead requires an analysis of the distributions of the random variables involved and their stability over time. To be useful, such quantification would need to predict an associated improvement in A_o at varying amounts of investment in critical consumable repair parts along the supply chain, and provide some estimate of the riskiness of such an investment. Therefore, this study was started based on the following research questions:

1) What is the impact to A_o when we reduce CWT for repair parts that deadline equipment?
2) What levels of investment can we make to reduce CWT in a cost-effective way?

B. PRE-POSITIONING CRITICAL REPAIR PARTS

One of the main purposes of the SMU is to reduce the amount of time it takes the operating forces to receive supplies. To do this the SMU forward positions inventory in

it warehouses fulfills customer orders out of stock first. The purpose of this study is to determine what benefit, if any, forward positioned stock has on A_o. To narrow the scope of our basic research questions, we limit our investigation to forward positioned stock as the solution. With this possible solution in mind, we established the following secondary research questions that will drive our study:

1) Can we model the variability in CWT for critical parts?
2) Can we capture the stochastic relationship between variability in CWT and A_o for deadlining parts in a simulation model?
3) How can we determine the validity of our simulation model?
4) What CWT thresholds should we examine for target reduction?
5) What should our desired service level be for part stocking criteria?
6) What improvements in terms of A_o will we realize on our investment in CWT reduction, and what is the riskiness of that investment?

As we build our methodology into a simulation model, we answer these questions in order to demonstrate the nature of the relationship between CWT and A_o.

II. BACKGROUND

The relationship between CWT and A_o relies on understanding a myriad of supply and maintenance terms, definitions, concepts, and processes. We first provide background information to lay a foundation for the link between CWT and A_o.

A. TERMS AND DEFINITIONS

1. Customer Wait Time

Customer Wait Time can be expressed as the time between all supply chain processes from the initial induction of a repair part into a requisition system to the receipt of the part by the initiating customer. The customer is the maintenance organization that will utilize the repair part to restore a Principal End Item (PEI) to a serviceable condition. For this study, the customer is either the organic level maintenance personnel at the operational battalion/squadron or the intermediate level maintenance organization when maintenance actions are passed to them. The final customer in the maintenance cycle is the battalion/squadron commander who is responsible for employing the PEI in the performance of assigned missions.

2. Equipment Readiness (R) and Operational Availability (A_o)

The terms operational availability and equipment readiness are closely related, yet are not exactly synonymous. These terms are used as indicators of the total amount of equipment that is available for use by the battalion/squadron commander. The readiness rate is defined as the state of a pool of assets that is available and ready to use in performing its intended functions, and is stated as the percentage of all assets that are fully mission capable (FMC) at a given time. The Marine Corps generally uses the term readiness, or R-Rating, to determine the percentage of equipment that is available for use. Readiness in the Marine Corps is determined using the following equation:

$$\text{Readiness \% (R)} = \frac{Possessed - Deadlined}{Possessed}$$

While readiness measures the number of assets available for use at a point in time, A_o is a measurement of the percentage of time an item is available under certain operating conditions (Jones, 2006). Both of these measures will change over time as operating conditions change and as items are brought in and out of a mission capable status. A_o is a function of the mean time between failure (MTBF) of an asset (or uptime), and the time that an asset is not available (or downtime) as follows (DoN, 2003):

$$A_o = \frac{Uptime}{Uptime + Downtime}$$

For our study, this maintenance downtime (MDT) is considered to be the time that an asset is not operational due to deadlining maintenance requirements. MTBF is calculated as the average number of days that an asset was operationally available for use between repairs. Downtime is measured as the mean time to repair (MTTR) plus administrative delay time (ADT) plus the time that the customer must wait for repair parts to arrive in order to conduct maintenance (CWT). MTTR includes all maintenance action time from the time that critical repair parts have been received and the date that an Equipment Repair Order (ERO) is downgraded to a non-deadlining ERO or the date that the ERO is closed. ADT includes time waiting for technical data, maintenance personnel and equipment availability, inspection time, time awaiting further actions, and the time lost due to human error. Bearing these factors in mind total downtime is calculated as follows (DoN, 2003):

$$Downtime = MTTR + ADT + CWT$$

Therefore, the A_o equation can be extended as shown below:

$$A_o = \frac{MTBF}{MTBF + MTTR + ADT + CWT}$$

3. National Stock Number (NSN)

Each repair part is assigned its own thirteen-digit National Stock Number. The critical repair parts that are required to ensure operational readiness are primarily Class IX, which is defined as “all repair parts and components, including kits, assemblies, and

subassemblies (reparable and non-reparable) required for maintenance to support all equipment" (MCO 4400.15E, p. 8–7).

4. Consumable Repair Part

This is a classification of Class IX which includes all items that are non-reparable and are discarded after use, and all items that are expended when used (Jones, 2006, p.18.1). This study will primarily focus on consumable repair parts that deadline equipment.

5. Secondary Reparable (SECREP)

Secondary Reparables (SECREP) are major components to end items that are repairable at appropriate maintenance echelons. While SECREPs are considered to be Class IX, this study will focus on consumable repair parts due to the varying stock determination methods between SECREPs and consumables as well as the varying general availability between SECREPs and consumables. SECREPS are also typically part of the initial sparing calculation provided in the contract when a PEI is fielded. Because SECREPs are not under the same cognizance as consumables, the scope of our study is limited to consumable repair parts. We desire a realistic representation of the impact that can be obtained by only pre-positioning consumables, given the impact that SECREPs also have upon readiness. Thus, we included SECREPs in the overall determination of readiness; however, we excluded them from the decision criteria for additional pre-position stock or modifications to CWT. This exclusion is based upon the Source, Maintenance, and Recoverability Codes (SMRC) as described in the *Joint Regulation Governing the Use and Application of Uniform Source Maintenance and Recoverability Codes*.

B. PROCESSES

1. The Marine Corps Legacy Maintenance Process

When a Principle End Item (PEI) ceases to operate or perform at a level necessary to conduct assigned tasks (shoot, move, or communicate) it is inducted into the maintenance cycle. Using the Marine Corps Integrated Maintenance Management System

(MIMMS), maintenance personnel at the operational battalion or squadron open an Equipment Repair Order (ERO). When an ERO is opened it is done so with a Non-Mission Capable Maintenance (NMCM) Indicator that identifies that the problem is now being determined and is in the hands of maintenance personnel. This NMCM Indicator signals the beginning of MDT, also commonly known as repair cycle time (RCT). Immediately upon induction, a maintenance technician performs a complete limited technical inspection (LTI) on the equipment to troubleshoot the problem with the item and determine what course of action is needed to repair the item. If the technician is able to return the item to full service, then he does so immediately. If the repairs required on the PEI are beyond the organic maintenance capability of a particular battalion or squadron, then it must be inducted to the next higher echelon of maintenance. Each MEF has a Maintenance Battalion where intermediate maintenance is conducted. Upon induction at this echelon of maintenance, the maintenance battalion technicians are required to open another ERO and must conduct an LTI on the equipment to determine the best course of action to repair the item according to their maintenance capabilities.

Whether at the organic (operational) or intermediate level, once the parts needed to restore the end item to serviceability are identified, the NSNs are recorded on an Equipment Repair Order Shopping List (EROSL). The maintenance technician passes this EROSL on to a supply clerk who signs the EROSL acknowledging receipt. The time it takes for the maintenance technician to deliver the EROSL to the supply clerk plus the time that passes before the supply clerk inducts the requisition into the supply system contribute to ADT. The life of this supply requisitions will be covered below, but once all maintenance actions are complete the ERO goes into a Non-Mission Capable Supply (NMCS) status indicating that the problem now lies in the hands of the supply system.

Once an ordered item is received, it is issued to the requesting maintenance section. When all needed parts ordered for one ERO are received, the status of the ERO is changed back to NMCM telling the commander that the equipment is still broken and it is a maintenance problem again. For critical repairs, maintenance personnel are required to return the item back to full service as quickly as possible and when all maintenance actions have been completed and the repair has been checked for both quality and

operability, the ERO is downgraded, if awaiting other less critical parts, or closed. The status change between NMCM and NMCS is designed to place ownership on the source that is responsible for the delay.

2. The Marine Corps Legacy Supply Requisition Process

Upon the receipt of the EROSL, the supply clerk assigns a Military Standard Requisitioning & Issue Procedures (MILSTRIP) Document Number to each NSN needed to repair the PEI. The document number is used to track the status of the requisition from order to receipt. Ideally, prior to the close of business on the day the EROSL was received, the supply clerk will enter each document number into the Asset Tracking and Logistics and Supply System (ATLASS) database, which converts EROSL data into MILSTRIP form, and will create and send this data to the SMU for processing into the Supported Activities Supply System (SASSY) mainframe. This marks the beginning of measurable CWT. The time it takes validate EROSL's, enter them into the ATLASS database, and submit them is another contributor to the ADT of the repair cycle of an asset.

The first stop for a requisition placed by units in the MEF is the SMU, which is the primary source of supply for repair parts. The I MEF SMU supports 86 units distributed across California and into Arizona. They carry over 22,000 National Stock Numbers (NSN) that represent more than $62 million in inventory. In their legacy supply interface, the SMU submitted requisitions via batch process into the SASSY mainframe at the end of the business cycle or once a day. This procedure adds on average one half-day to the lead-time for these requisitions.

The SMU stocks Class IX repair parts either based on previous demand or in some cases when repair parts are pushed to the SMU in anticipation of demand for newly fielded items. If a repair part is not stocked by the SMU, the requisition will be passed to the wholesale supply level within the Defense Automated Addressing System (DAAS) for fulfillment at one of DoD's National Inventory Control Points (NICP's) (Bates, 2005). The DAAS Center (DAASC) is a huge data processing center that operates 24 hours a day, 365 days per year and processes all requisitions for the entire DoD (Bates,

2005). DAASC will determine the best source of supply (SOS) to source the needed item and will route the requisition to that SOS for fulfillment. The NICPs include such entities as the Defense Logistics Agency (DLA), the General Services Administration (GSA), and the U.S. Army Tank-automotive and Armaments Command (TACOM). If the SMU stocks a repair part, but does not have the part on hand when a requisition is submitted, the SMU will issue a backorder for the item and issue the part when the item is replenished in their stocks. Once the ordering unit receives the repair part from the SMU or from other channels, the part is delivered to the maintenance section that ordered it. Measurable CWT for that particular document ends when the package exchanges hands and the transaction is recorded in ATLASS and submitted to SASSY. The time it takes to hand off the item, as well as to process the appropriate receipt transaction is another contributor to ADT.

III. LITERATURE REVIEW

In 2000, the Department of Defense (DoD) implemented CWT as a metric for measuring the end-to-end supply chain effectiveness with DoD Instruction 4140.61. Since then, the DoD has been trying to measure its effective implementation and has aimed at tying the impact of CWT's effect on material readiness. The relationship between the variables is apparent; CWT resides within the denominator of the A_o equation. To find a starting point for measuring the benefit of forward positioned stock, a review of other attempts at identifying the relationship between CWT and A_o is necessary. There are three significant cases that aided in our determination to use simulation analyze the impact between A_o and CWT.

A. DIAGNOSING THE ARMY'S EQUIPMENT READINESS: THE EQUIPMENT DOWNTIME ANALYZER (EDA)

In August of 2002, the U.S. Army sponsored a study by the RAND Corporation to gain some insight into how equipment readiness is affected by stock held by their Supply Support Activities (Peltz et. al, 2002). RAND's study found that the Army had difficulty linking the logistics process to equipment readiness. To solve this problem RAND developed the Equipment Downtime Analyzer (EDA), which is a relational database that ties maintenance events to supply chain performance (Peltz et al., 2002). The focus of the EDA is to break down all the events that drive "broke-to-fix" time to identify problems so they can be resolved. The authors argue that resolving these problems will intuitively reduce MDT and as a result will increase readiness.

During their study of the Army's maintenance reporting capabilities, Peltz et al. (2002) found that the Army's readiness numbers were expressed as Not Mission Capable (NMC) rates and were derived by taking the product of average end item repair time and the item failure rates. The Army's supply and readiness reporting systems only tells what is broken, but does not mention how many times items have failed or the duration of their failure (Peltz, 2002). Like the Marine Corps' current method of readiness reporting, the Army reports its readiness numbers monthly via the Defense Readiness Reporting System (DRRS). Solely using readiness information on a monthly basis made it difficult

to distinguish between operational time and garrison time (Peltz et al., 2006). As a result, the study deemed that finding the relationship between CWT and Readiness was "impossible (Peltz et al., 2002 p. Xiii)" with the data collection methods the Army was using. The main purpose of the EDA is to provide a means whereby the Army could focus resources where they had the greatest impact on equipment readiness (Peltz et al., 2002) and that A_o is intuitively improved as we reduce CWT.

Legacy readiness reporting in the Army is highlighted by looking at availability as a monthly number that is aggregated amongst all items a unit possesses. Peltz et al. (2006) found that daily measurements of readiness rates fluctuated dramatically around the averages reported. This variance showed that *readiness* as a reporting metric was misleading, and did not accurately tell a Commander what percent of his assets would be available during a given time period or during operations. This section of their research led us to look beyond averages and incorporate the use of variability of CWT into this project.

In their study, Peltz et al. (2002) highlight that the demand signal for repair parts is not continuous within DoD due to the fact that training schedules are not continuous, and equipment does not have steady utilization rates. This erratic demand leads to erratic patterns in equipment readiness. As a result, the DoD experiences periods of intense ordering and maintenance, followed by lulls. Prior to an exercise, readiness tends to be high; conversely, following an exercise, it drops. This drop generally serves as the trigger for periods of aggravated demand for DoD (Peltz et al., 2002).

Despite their model being able to identify maintenance events for repair parts that should be stocked, Eric Peltz and his team found that there was "no way to measure whether a reduction in wholesale requisition wait time (RWT) flows through the system to produce an equivalent improvement in equipment readiness" (Peltz et al., 2002). The next major study into the relationship between CWT and Readiness came in 2007, when the DoD Inspector General directed a commission report on the progress of DoD Instruction 4140.61.

B. DOD IG UNIFORM STANDARDS FOR CUSTOMER WAIT TIME

In July of 2007, the DoD Office of Inspector General submitted a report to Congress entitled "Uniform Standards for Customer Wait Time." The fact that Supply Chain Management has been identified as one of the high risk areas within the DoD since 1990 is what generated the need for such a report (IG, 2007). This report serves as a report card on the progress of CWT implementation in DoD.

From Operation Desert Storm, when DoD faced an average CWT of 49 days, through 2006, when CWT was reported to average 21 days, supply chain improvement has been an arduous task (Gansler, 2007). The commission's report cited DoD's goal for CWT as 15 days for both the Army and Marine Corps in 2006. Fifteen days may be considered unsatisfactory when compared with the civilian benchmark of 1–2 days for domestic CWT, and 2–4 days for international CWT (Gansler, 2007). During their analysis, the IG found holes in reporting requirements, and was unable to show the relationship between CWT and readiness.

To measure the effectiveness of DoD's CWT implementation, the DoD IG conducted a full-blown statistical analysis that sampled 1,150 Army requisitions and 773 Marine Corps requisitions to test conformance with CWT criteria. The study found that the Army conforms to DoD Instruction 4140.61 by leaps and bounds ahead of the Marine Corps. The Army was found to have 67% of its requisitions recorded correctly, 29% not recorded in a timely manner, and 4% not properly vouchered. The Marine Corps, on the other hand, was found to only have 3% of its total requisitions recorded properly, 86% recorded late, and 11% not properly vouchered. This study revealed that 6 years after the implementation of DoD Instruction 4140.61, the various services were still not on the same page when it came to supply chain management and logistics transformation.

The second major revelation the IG study provided was that "DoD Officials could not link CWT to operational Readiness" (IG, 2007). The IG Report cites the improper categorization of requisitions as the cause of this problem, namely the lumping of both high and low priority requisition together. DoD Instruction 4140.61 did more than establish CWT as a measurement; it directed monthly reporting of both readiness and CWT numbers from all services. This directive was interpreted in different ways by each

service, and because the directive was not supervised properly the numbers used were dramatically different. One example of the confusion with the directive is exemplified in the manner by which the Marine Corps determines CWT and submits its report. MarCorLogCom consolidates all requisition data across the three SMUs and submits their report at the enterprise level as one batched mix. They do not report CWT based on each of the independent supply activities they manage (IG, 2007).

Since all of the data the IG used to measure CWT and readiness came in different terms, the task of correlating the variables, and modeling the impact that CWT has on readiness was deemed impossible. The IG's trouble with analyzing data and in correlating the variables is what led this study to solve the problem through simulation. If experts in the past have struggled with the data to arrive at a useful correlation based on reported CWT information, our study bridges the gap and uses actual requisitions from raw data to derive CWT, and simulate its impact on the A_o equation.

The Marine Corps itself currently manages 5 major separate supply chains (each of the three CONUS SMUs, Afghanistan, and centralized SECREP management). As such, the correlation between A_o and CWT can truly only be tackled by isolating one of these supply chains, and further ascertain how that supply chain supports one weapon system. This approach is where our study continues beyond the point where the IG left off.

C. STOCK DETERMINATION MADE EASY: THE ENHANCED DOLLAR COST BANDING MODEL (EDCBM)

In the July-August 2007 edition of Army Logistician, the article "Stock Determination Made Easy" was published to discuss the "Enhanced Dollar Cost Banding Model" (Girardini, Lackey, & Peltz, 2007). The EDCBM is simply an extension of the EBA model. Like the EBA, the EDCBM is a relational database capable of drilling down to what items are needed, but then expands its capability in stock determination. The model is capable of taking limited resources and it prioritizes what items should be stocked based on weight, cube, cost and variability in wholesale lead times. This model focuses on CWT goals, and combines the capability of the intermediate supply support activity with the lead times from the wholesale supply activity to set CWT within certain

thresholds. To understand the model, it is helpful to know its origins.

The U.S. Army stocks repair parts at the intermediate level called Supply Support Activities (SSA), where each SSA stocks the necessary NSNs outlined in an authorized stocking list (ASL) to support a Brigade Combat Team (BCT). Studies by the RAND Arroyo Center concluded that higher fill rates from the Army's ASLs resulted in direct positive effects on equipment readiness. One RAND Arroyo Center study determined that a 10 percent improvement in the ASL fill rate resulted in a 4 percent increase in equipment readiness (Girardini et. al, 2007).

In 1998, the RAND Arroyo Center developed Dollar Cost Banding (DCB), which expanded the ASL focus in three areas (Girardini et. al, 2007). First, DCB did not focus solely on historical demand, but considered the criticality of an item as a basis for stocking it, even if it experienced low demand. Cost and size were also factors, with DCB lowering the risk of a deadline by stocking lower cost, smaller items that would affect readiness. DCB also moved beyond the days of supply method of stocking parts and considered the variability in demand of individual NSNs in order to achieve acceptable CWT goals. Lastly, DCB automatically excluded non-critical items or items that the customer could afford to wait for which focuses the SSA resources on those critical items that affect readiness (Girardini et. al, 2007).

The EDA assisted in the development of the Enhanced DCB (EDCB), which narrowed the list of parts that were true readiness drivers. This allowed the SSAs to focus even more on criticality and reduce resource allocation of storage space and initial inventory investment. Operation Iraqi Freedom interrupted the expansion of EDCB. Home-station requirements experienced variability in demand based on training exercises when equipment was most used. Since home-station requirements were used to develop ASLs for SSAs in Iraq, fill rates plummeted as deployed operations approached a steady state. The deployed SSAs that implemented EDCB experienced improvements in fill rates and CWT over those that did not implement the program.

The significance of DCB and EDCB was not that fill rates increased, but that CWT for critical repair parts decreased along with the ability of maintenance personnel to repair equipment more quickly. This ability to repair items more quickly would

intuitively lead to increased readiness rates. While this clear result of refocusing the stocking criteria led to these ideological outcomes, there was no measurable link established to show how the reduction in CWT related to the increase in readiness levels. Our study will refer to methods of ideal stocking criteria, but will take the next step of showing how the identification of critical parts and pre-positioning of them in the supply chain will effect a decrease in CWT, and allow us to measure the relationship between CWT and equipment readiness.

D. TARGETING INVENTORIES TO AFFECT GROUND EQUIPMENT READINESS

The concept of targeting repair parts that add the most to equipment down time for stocking is no new concept. In his 2002 article entitled *Targeting inventories to affect ground equipment readiness*, Major Brandon McGowan attests that the current stock methodology of the SMU does not account for the fact that not all PEI's are created equal. McGowan's article loosely covers what the SMU's current stock method is, and how it misses the mark for critical end items and does not address the impact of stock decisions on readiness. Major McGowan is both insightful and forward thinking in his solution to this problem, which amounts to categorizing items based on commanders precedence and assign those items a higher service level for material held at the SMU.

According to McGowan (2002) the SMU stock policy is to stock items with a certain level of demand within a certain time period. Once items have passed the demand requirement then they are all stocked according to the same generic formula with no adjustment for the importance of the item they are stocked to support. The SMU's inventory level accounts for both the demand and lead-time of the item from wholesale supply. McGowan argues that the flaw in this logic is that when providing the same service to a radio, which the marine corps has an abundance of, and a tank, which is low density, does not address the relative importance of these items to commanders. It is clear that a commander would care more about the tank being deadlined or degraded than the radio, and McGowan believes he has an answer to this problem.

McGowan's solution to the problem is to subcategorize items using the integrated logistics capability (ILC) quadrant model, and to add weight to items with degraded readiness reporting numbers. The ILC model categorizes the importance of items based on their mission value and uniqueness. There are four quadrants used in the model, which are listed below:

Quad 1: Bottleneck Items – Low mission value and low substitutability

Quad 2: Critical Items – High mission value and low substitutability.

Quad 3: Leveraged Items – High value and high substitutability

Quad 4: Routine Items – Low value and high substitutability.

McGowan insists that items stocked at the SMU should be given a different service levels based on where they fall within this model. McGowan also provides that aside from equipment ILC categorization, the SMU must consider the current readiness rate of individual items to determine service levels. By assigning items a threshold of unacceptable readiness, we can target improved readiness of those items through forward positioning of repair parts with increased service levels.

Major McGowan clearly understands that the SMU has the capability of significantly improving readiness through stocking the appropriate critical repair parts. In 2002, McGowan confirms that the Marine Corps already has the tools needed to measure MEF readiness and track supply chain performance, but his article only describes the relationship between CWT and A_o as intuitive. McGowan believes that when we stock material based on demand and ILC categorization instead of demand alone that higher service levels will increase MEF readiness. A model that will show the impact of our stock decisions on A_o would certainly lend to Major McGowan's study.

E. CONCLUSION

Many attempts have been made at tying CWT to readiness. While both the EDA, and EDBC models were effective at improving the responsiveness of supply support activities, they did not provide the means whereby CWT and readiness could be married. In addition, the DoD IG set out to use methods that were established by their very own directive, and found that at the DoD level, the information is too aggregated with far too

much variation in the way each service goes about recording both CWT and readiness.

Based on what we know about past attempts to correlate readiness and CWT, this study will take a different approach to solve this complicated problem. The remainder of this report aims to solve this problem at the lowest echelon possible; this issue is not one for DoD, the Navy, the Army, or even the Marine Corps as a whole. What the EBA and EDCB models have shown is that this is an issue best solved through the lens of a singular end item operating in a specific area of operations. CWT for any given NSN will vary among different locations. NSN and PEI failure rates also vary among locations due to operational tempo and the physical climate. Therefore, our attempt at quantifying this relationship focuses on a specific geographical region with an individual end item, not the enterprise level.

The key to showing the relationship between CWT and readiness lies in the A_o evaluation itself. Using that equation and simulation modeling, this report intends to show that for a certain level of investment, decision makers can expect a certain level of readiness improvement. The remainder of the report describes how to simulate $A_{o,}$ how to simulate the impact of investment in CWT reduction, and analyzes the results of these reductions.

IV. METHODOLOGY

To establish the relationship between CWT and A_o, we had to compare the historical state using actual CWT with predictions from our model. Once the relationship was established, the main goal of our analysis was to predict a future state of reduced CWT that could be attained if our prescriptions regarding forward placement of inventory were followed. In so doing, we simulate and compare effects on A_o between the "As Is" and the "To Be" model outputs.

A. DATA SOURCES AND COMPILATION

This analysis is focused on identifying critical repairs for Mission Essential Principal End Items (PEIs) from I MEF that are the result of a deadlining event. The Marine Corps lists all Mission Essential Equipment within the annual Marine Corps Bulletin 3000 (MCBUL 3000) Table of Marine Corps Automated Readiness Evaluation System (MARES). Equipment listed on the MCBUL 3000 is selected by Headquarters Marine Corps in order to provide an appropriate measure of the equipment condition and preparedness for the Marine Forces (MCBUL 3000, 2011). We thus narrowed our selection of candidate PEIs based on the MCBUL 3000.

In September 2011, the Commandant of the Marine Corps, General James Amos, provided a memorandum to Secretary of Defense Leon Panetta. With future defense capability reduced in a world that presents increasing threats to the national security of the United States, General Amos highlighted the ongoing need for the expeditionary and amphibious nature of the United States Marine Corps (CMC, 2011). As the withdrawal from Iraq is complete and preparations begin for the withdrawal from Afghanistan, the Department of Defense has shifted its focus to the Pacific Area of Operations. As a result, the Marine Corps will increase its focus on amphibious operations and training. Therefore, we selected the Marine Corps Amphibious Assault Vehicle (AAV), delineated under the Table of Authorized Material Control Number (TAMCN) E0846, to conduct our analysis. This weapon system will likely see increased usage in the near future, and its operational availability will become critical to operational commanders.

Data for this study came from several resources, including the Navy Supply Systems Command (NAVSUP) Birdtrack database, the Marine Corps Equipment Readiness Information Tool (MERIT), the I MEF SMU aboard Camp Pendleton, CA, as well as MIMMS and SASSY databases. Data from the latter two systems has been consolidated by Marine Corps Logistics Command (MarCorLogCom) into the Master Data Repository (MDR). Data from MIMMS provided the necessary maintenance information to determine how long equipment was deadlined, i.e., unavailable. Data from SASSY gave us the requisition receipt dates for all parts ordered on ERO that were opened in MIMMS. Birdtrack provides inventory positioning, asset visibility, and customer wait time analysis that allowed us to obtain additional observations of critical NSN wait times, namely all requisitions that were passed to one of the National Inventory Control Points (the wholesale supply level).

MarCorLogCom and Marine Corps Systems Command (MarCorSysCom) developed the Life Cycle Modeling Integrator (LCMI) that contains various tools to analyze readiness and maintenance factors for Marine Corps ground equipment. One tool within LCMI is the System Operational Effectiveness (SOE) application that allows commanders and logistics personnel to analyze data retained in the MDR. The SOE provides current and historical maintenance and supply information that can assist decision makers in identifying trends, averages, and variability for maintenance and supply actions. The SOE can also assist in analysis of past events that can be applied to forecasting decisions on maintenance and supply actions. The SOE can thus be used as a Decision Support Tool. The SOE provides data in several formats that allows for specific analysis that we discuss throughout this study.

Beginning in 2010 the Marine Corps began its transition to an enterprise resource management system known as Global Combat Support System – Marine Corps (GCSS-MC). This study covers all maintenance actions and corresponding requisitions for critical repair parts for all deadlining events of AAVs in I MEF from January 1, 2009 through December 31, 2011. While the new system provides real time and up to date data information, our data was obtained primarily from the pre-GCSS-MC legacy systems (MIMMS and SASSY). We decided upon this course of action because GCSS-MC was

not fully fielded at the time of our study. The data and processes described within this study are based upon these legacy systems, which were in place from January 2009 through the beginning of implementation of GCSS-MC for 3d Amphibious Assault Battalion aboard MCB Camp Pendleton in November 2011.

MarCorLogCom provided us with a data set from the MDR that included all maintenance action and supply requisition data within I MEF from 2009 – 2011. Our analysis of these raw data files allowed us to identify all critical repair parts, degrees of variability in requisition wait times for those critical repair parts, and the effects of investments in re-positioning repair parts forward in the supply chain. Additionally, we identify the length of time an asset was deadlined relative to the CWT of the repair parts required to bring it back to serviceability. The data collection of this study was limited to three years since stocking criteria over longer periods of time usually changes. As a result, CWT also changes between periods as stock methods are adjusted, and thus skews our analysis the further back we go. Limiting our study to three years provides sufficient breadth and depth to make this study relevant and applicable for future decision making, and allows us to capture the most recent and consistent data possible from the legacy systems.

When identifying the repair parts required to ensure operability of equipment, Combat Essentiality Codes (CEC) are assigned to each NSN to identify its criticality. Filtering requisition data by CEC was necessary in our methodology to identify only those NSNs that would have an impact on the operational readiness of an end item. As listed in the below table, we limited our data analysis to only the repair parts that had a CEC of 5 or 6. Failure of CEC 5 or 6 parts renders an end item unserviceable, and thus unable to perform its intended mission. Table 1 lists the definitions of CEC 5 and 6 (USMC, 1984, p. 4–4–20).

Table 1. Combat Essentiality Codes
USMC, 1984, p. 4–4–20

Code	Definition
5	Critical Repair Part to a Combat-Essential End Item: Those parts or components whose failure in a combat-essential end item will render the end item inoperative or reduce its effectiveness below the minimum acceptable level of efficiency.
6	Critical Repair Part to a Non-Combat-Essential End Item: Those parts or components whose failure in a non-combat-essential end item will render the end item inoperative or reduce its effectiveness below the minimum acceptable level of efficiency.

The CEC coding system is a standard, and may not be accurate all of the time due to its inflexible nature. Some repair parts on the AAV are coded with CEC 6, even though according to UM 4400–124, these parts are intended for non-combat essential end items. Therefore, we combined this factor with Non-Mission Capable Supply (NMCS) Indicators to provide a more accurate picture to determine which assets were actually deadlined. Maintenance technicians are required to input the NMCS Indicator when they order a repair part on the Equipment Repair Order Shopping List (EROSL) to identify how important their supply requisitions are. NMCS indicators relate to the priority code of the requisition. Priority codes range from 01 to 15, with 01 being the highest priority for units in a combat zone and 15 being the lowest priority for routine items ordered by units outside the Fleet Marine Force and the Reserves. Our study limits the requisitions with priority codes between 01 and 06, which scopes our analysis to only critical requisitions for the operating forces within I MEF.

Definitions of NMCS Indicators are listed in TM 4700–15–1, Ground Equipment Record Procedures (1992). We limited our analysis to those maintenance actions with NMCS Indicators of 9, N, and E. NMCS code 9 refers to requisitions with a priority designator of 01, 02, or 03 for an OCONUS customer or a CONUS customer deploying overseas within 30 days. NMCS Code N refers to requisitions for deadlining items with priority designators of 02, 03, 04, 05, 06, 07, 08, 09 for a CONUS customer or 05 for an OCONUS customer. These codes identify a readiness reportable item or an item deemed

by the unit commander as mission essential to be in a deadlined state as a result of a critical repair part failure. NMCS Code E is used for requisitions with priority designators of 02, 03, 04, 05, 06, 07 or 08 when the PEI is expected to be deadlined in 15 days for a CONUS customer or within 20 days for an OCONUS customer. While NMCS Code E does not represent an actual deadlining event, requisitions with this code are shown to be critical that will result in a deadlined PEI. Thus, these items are critical to the operation of the vehicle and results in a deadlining event. Therefore, they are included in our analysis on demand and parts stocking criteria.

Our data analysis began with 2,315 EROs, consisting of 5,294 requisitions for all AAVs in I MEF during the 2009 – 2011 time period. When we filtered the data to only include deadlining maintenance actions, we discovered that 1,647 of those EROs were maintenance actions that resulted in the deadlining of an AAV. These 1,647 ERO's included 3,027 requisitions for repair parts, which represented 202 NSNs. Of the 202 NSNs identified in our study, 164 were Class IX consumables and 38 NSNs were SECREPs.

Using the SOE, we determined the mean time between failures (MTBF) for the AAV by extracting all deadlining maintenance events for all serial numbers within I MEF from 2009 - 2011. Although readiness data can be obtained daily, the Marine Corps reports readiness monthly in the Defense Readiness Reporting System-Marine Corps (DRRS-MC), a subset of DRRS. We thus chose 30 days as the basis for determining readiness and asset availability in our model. Subsequently, using the reliability equation, we determined the reliability and probability of failure of the AAV for I MEF for a 30 day period. Thus, our simulation model represents the possible outcomes of A_o for a 30 day period.

Mean Time to Repair and Administrative Down Time (MTTR + ADT) in our study includes all actions taken before a part is ordered, and after the repair part is received to bring an item back to full service. To determine MTTR and ADT, we obtained the total Maintenance Downtime (MDT) for deadlined assets from the data we obtained from MarCorLogCom for each ERO originating in I MEF between 2009 and 2011. Without analyzing actual hard copy EROs, EROSLs, and supply documentation,

we were unable to derive what fraction of the elapsed time belonged to each of these variables separately. For simplicity in this study, we have combined MTTR and ADT into one variable based on actual data we have available. We then determined the maximum CWT for each ERO. This maximum CWT represents the amount of time it took to receive all repair parts ordered under one ERO. Therefore, the MTTR + ADT variable was determined by summing the difference between the total MDT and the maximum CWT for each ERO, then dividing this sum by the total number of EROs.

$$MTTR + ADT = \frac{\sum(MDT - \max CWT)}{n}$$

Where n = number of EROs.

Table 2 displays the results of our calculations for MTBF, reliability probability, probability of failure, and MTTR + ADT.

Table 2. Maintenance Variables
I MEF, 2009 – 2011

TAMCN	Nomenclature	MTBF (in days)	Reliability (30 days)	Probability of Failure (30 days)	MTTR + ADT (in days)
E0846	Assault Amphibious Vehicle, Personnel AAVP7A1	188.5	85.29%	14.71%	7.36

The data from the MDR obtained from MarCorLogCom contained all requisitions for deadlining maintenance events for AAVs from 2009 – 2011. To create our model, we identified each critical repair part NSN that I MEF received for the AAV. Since some NSNs were received from both the SMU and the wholesale level for different requisitions, the CWT from each source varies. Thus, we determined the average and standard deviation of CWT based on the weighted average of the requisitions filled by the intermediate and wholesales supply levels, which we discuss in greater detail later in this chapter.

B. MODEL

After an analysis of the data, the next step in demonstrating how changes in CWT impact A_o was the creation of a simulation model. This was our chosen method because the previous attempts by the RAND Corporation and the GAO were unable to quantify these two variables. The model we created is intended to demonstrate how varying amounts of investment in reducing CWT will improve $A_{o.}$ Our model was built using Microsoft Excel and Oracle's Crystal Ball® simulation software, which is a Monte Carlo-based simulation software that can be used for predictive modeling, forecasting, and optimization. Crystal Ball® is also used in this analysis to estimate the reduction of risk associated with the pre-positioning of critical repair parts.

The model incorporates actual data and the A_o equation to show the "As-Is" process and compares it with the "To-Be" position (based on hypothetical re-positioning of repair parts based on historical data). Since readiness is reported monthly via the DRRS-MC data repository, our model likewise is a snapshot of readiness and failures per month. To feed the model, we created a data set that contains all required historical maintenance and supply actions from 2009 – 2011. Next, we describe the simulation model inputs and output measures in detail.

1. Model Inputs

In this section we discuss the key input fields to our model and provide some clarity regarding why we used these fields, and how they can be used to manipulate the model.

a. Mean Time Between Failure (MTBF)

The MTBF for an AAV was derived from the SOE as stated above. The MTBF calculation is particularly important to any model used to calculate A_o, since it is used to predict what the systems reliability will be in the time period the model is set to cover. Every effort should be made to ensure this data comes from the most reliable sources.

b. Probability of Failure

According to the Operational Availability Handbook, the average failure rate of an asset, or λ, identifies the expected number of failures within a given time period, and is determined by 1/MTBF (DoN, 2003). Reliability of a system is commonly assumed to follow an exponential distribution, so reliability over a period of time *t* can be expressed with the cumulative exponential probability at time *t* (Blanchard, 1998, p. 38):

$$R(t) = \exp^{-\lambda t}$$

Since this is a cumulative probability, this is the probability the system has not failed *before* time *t*. The probability the system will fail after a period of time *t* is determined by the complement, or 1 – R(*t*). The probability of failure of an asset determines how often an individual asset fails. Based on operating conditions, the reliability of a system rises and falls and can be adjusted for known changes in operations commitments.

To determine the probability of failure of an asset during a month under normal operating conditions we used the reliability equation, $R(t) = e^{-\lambda t}$, where *t* represents usage in days. For our model we represented *t* as 30 days; however, this rate can be altered without affecting the accuracy or reliability of our model. Using the probability of failure in this manner allows for this model to accurately predict A_o under varying operating situations.

c. MTTR + ADT

In this portion of the header we input the average MTTR + ADT that was derived as described in the data section above. To capture the variability in MTTR + ADT, we attempted to use goodness of fit statistics to apply to the data we obtained. However, no distributions suitably fit the MTTR + ADT values in our data. While the lognormal distribution was often determined to be the best fit of those tested, no single distribution was determined to provide a sufficiently accurate fit. This caused us to err on the side of a more conservative and penalizing assumption. Therefore, we used the exponential distribution for MTTR + ADT. The exponential distribution is conservative,

in that it is unlikely to understate the risk of a long wait, since it has a high coefficient of variation (CV). The parameter for the exponential distribution is the reciprocal of the MTTR + ADT.

d. Data Set

The data set we created to build our model consists of 202 NSNs with information that is both predictive and informative. For this section we focus primarily on the informative nature of the data set. More details pertaining to the data set are discussed in the simulation portion of the model description.

(1) Header Information. The header information used for this model includes fields for NSN, Nomenclature, Unit of Issue (UI), Unit Price in dollars (UP$), SMRC Code, and CEC Code for each item.

(2) Probability of Requisition Lookup Columns. In order to create a situation where the simulation randomly selects an NSN based on its likelihood of being requisitioned, we created a cumulative lookup column using Excel's "lookup" function. To do this, we determined the probability that an NSN would be ordered by dividing the number of times the item was ordered by the total number of documents requested. We then created a cumulative field that returns the sum of all probabilities, and created a column labeled "lookup" to search within the column based on Excel's random number function. We discuss the use of this column in the CWT calculator section below.

(3) SMU and Wholesale CWT Data. The next pieces of information we needed were the actual SMU and wholesale CWT data for all AAVs in I MEF from 2009 - 2011. These fields contain the count of total requisitions ordered, the quantity demanded at both intermediate and wholesale level, the average customer wait time (ACWT), the StDev of CWT, and the coefficient of variation (CV) for CWT at each level. This is the information that we later use to predict how CWT affects the system as it currently is. One problem we encountered was applying a valid StDev for instances when we had less than 10 observations of CWT. Whenever there were less than 10 observances for CWT, we used the CV of all valid observances to determine the StDev of

CWT for those instances. In this manner, we set the average variability of parts lacking sufficient observations to the average variability for parts that had sufficient observations.

(4) Additional Wholesale CWT Data: In addition to those documents for AAVs that passed through the SMU to the wholesale level that we captured above, we also pulled in all requisitions for our identified deadlining NSNs that reached the wholesale level for all customers and end items using NAVSUP's Birdtrack database. The CWT from this data was then entered into our model so that we would have a clearer picture of what to expect at the wholesale level in regard to service and wait times. Like the CWT data used above, this data included document number count, total quantity ordered, ACWT, StDev of CWT, and CV.

2. Simulating the present ("As Is")

To properly show how CWT affects A_o we use random variables to simulate how the different components of the A_o equation change within the different levels of the supply chain. In this next section we discuss the central formulas used to build our model. In addition to simulating the present, there are certain shared fields between the present and the future that will be discussed in detail below.

a. End Item Field

Our model begins with a simulation of the operational availability of an individual AAV. The Logistics Management 2nd Generation (LM-2) Unit Report data as reported in MIMMS provides historical readiness rates for the MARES Reportable Assets and also identifies the number of assets on hand in I MEF during the time period of 2009 – 2011. These numbers fluctuated during our analysis period, so we used the average number of AAVs possessed by I MEF as the quantity for our model, which is 216 AAVs. Our simulation is based on this pool of assets, representing the real population of AAVs. Each of the 216 AAVs is represented in one row within the model. The model simulates the effects upon each individual AAV for the "As Is" and "To Be" A_o and R Ratings during a simulated 30-day period. To replicate these fields for other assets under real conditions, one can simply modify the number of rows to match the number of assets that the target unit possesses.

b. *Failure Simulator*

The next column in the model is the failure generation column. Using the probability of failure of an AAV based on the 1 – R(*t*) equation, we set failure determination to randomly occur using Excel's random number generator function (*RAND*). The equation used in our model to trigger failures is as follows:

$$= if\,(RAND() < P(FAILURE), 1, 0)$$

This Excel function is used to determine whether an asset failed or not within our simulated 30 day period. The random variable function delivers a random number between 0 and 1 for each step of the simulation. The Excel *IF* function then determines if the asset on each row fails during a 30 day period. If a random number above the failure probability is randomly selected within Excel, the model simulates that an asset did not experience a deadlining event in that month, and thus did not fail. If an asset does not fail during the month, the model places a numeral 0 in the cell. No further changes are made across this row for this individual asset during this step of the simulation. If a random number below the failure probability is selected, the model simulates that an asset experiences a deadlining event, and thus has failed. If the asset fails, a numeral 1 is placed in the column and thus signals additional actions in subsequent cells to determine MDT. This field is incorporated into both the "As Is" and "To Be" models.

c. *CWT Look Up*

In the data section, we discussed that there are 202 different NSNs that are reported to have caused AAV failures between 2009 and 2011 with each having a probability of being ordered. When an AAV is determined to fail based on the failure generator above, the model uses the Excel random function to determine which NSN is selected to be requisitioned. The model uses the lookup function to identify the NSN row associated with this random number that is in the lookup column. The values in the lookup column are derived based on the probability of that NSN being ordered and the cumulative distribution discussed above. This method allows us to randomly select NSNs when an item fails within the model. This function signals that any time an item

fails during the month, the model looks up a random number, and return the CWT of the item that corresponds to the random value selected within the cumulative distribution.

Table 3 is an illustration of how the lookup table is set up. For example, suppose that the random number selected by Excel is .0588, the lookup function finds the value within the lookup column that corresponds to this value. To accomplish this, the model will first find the two values that this random number falls between. It then selects the lower value, which in this case belongs to NSN 2520–01–459–7021. Once the identified row is selected, the lookup function returns the CWT value associated with the selected NSN (11.45 days in this case) to be input into the CWT cell for the AAV that failed during this simulated month. More detail is forthcoming in the Calculated A_o section below.

Table 3. Excel Lookup Function Example

NSN	Nomenclature	Doc # Count	P(Requisition)	Cumulative	Lookup	CWT
1240013876727	PERISCOPE BODY ASSE	4	0.00132	0.00132	0	17.78
1240013876728	PERISCOPE HEAD ASSE	21	0.00694	0.00826	0.00132	7.42
1240013876729	PERISCOPE ELBOW ASS	14	0.00463	0.01288	0.00826	30.33
1240015535866	THERMAL SIGHTING SY	2	0.00066	0.01354	0.01288	10.42
1240015535870	HEAD ASSEMBLY,AAV	54	0.01784	0.03138	0.01354	46.22
1240015536111	INTERMEDIATE BODY	24	0.00793	0.03931	0.03138	4.38
1240015536957	THERMAL IMAGER SDU	17	0.00562	0.04493	0.03931	122.44
1240015541735	THERMAL ELBOW	41	0.01354	0.05847	0.04493	43.24
2520014597021	YOKE,UNIVERSAL JOIN	3	0.00099	0.05946	0.05847	11.45
2520014597028	YOKE,UNIVERSAL JOIN	1	0.00033	0.0598	0.05946	10.98
2520014597041	UNIVERSAL JOINT,VEH	6	0.00198	0.06178	0.0598	14.25
2520014723051	TRANSMISSION ASSY,5	15	0.00496	0.06673	0.06178	24.26
2520014726681	TRANSMISSION AND CO	116	0.03832	0.10505	0.06673	5.4
2520014728956	TORQUE CONVERTER	2	0.00066	0.10572	0.10505	2.63
2530011024540	TRACK ADJUSTER	23	0.0076	0.11331	0.10572	3.78
2530011024713	WHEEL,SOLID RUBBER	34	0.01123	0.12455	0.11331	16.08
2530011024714	WHEEL,SOLID RUBBER	9	0.00297	0.12752	0.12455	23.15
…	…	…	…	…	…	
6150015783251	WIRING HARNESS	10	0.0033	0.99835	0.99504	4.66
6150015858583	WIRING HARNESS,BRAN	3	0.00099	0.99934	0.99835	78.82
6350014307176	SENSING ELEMENT	2	0.00066	1	0.99934	16.54
			1			

Like the failure simulator, the probabilities are based on historical observations, not the assumption of any arbitrary probability distribution. So, this method places a higher weight on parts with higher demand as the distribution of the lookup selection is larger for those items, and smaller for low demand items. The weights are set in the exact proportions that demand occurred in the historical data. Once the NSN that fails is selected, the model uses Crystal Ball® to determine the actual CWT value to place in the CWT field. Data for this field is built in under the Data Set for each NSN to return a random variable, as discussed in the following section.

d. Consolidated CWT "As Is"

In order to gain an accurate picture of what CWT to expect under the past conditions, we separated all requisitions based on the source of supply, whether from the SMU or the wholesale supply chain. We then calculated actual fill rates, total document count, total quantity ordered, weighted average CWT (based on fill rate for each NSN), and finally a Crystal Ball Assumptions Cell. In the following sections we discuss each in greater detail.

(1) Actual SMU Fill Rate. The actual fill rate used was derived from the SMU perspective by taking the number of requisitions filled by the SMU, and dividing that number by the total number of requisitions made for that NSN.

(2) Total Document Count. This field was built simply by adding the documents that were filled by the SMU and the Wholesale Inventory levels during our 3 year research period.

(3) Total Document Quantity. This field is derived by taking the sum of quantities fulfilled at both the SMU and wholesale level over our 3-year research period.

(4) Consolidated ACWT. To arrive at a consolidated ACWT, we had to take the ACWT from the SMU and add it to the ACWT experienced when a requisition passes to the wholesale level. The formula used for weighting and adding ACWT's is as follows:

$$\text{Consolidated ACWT} = (\text{SMU Fill Rate})*\text{ACWT}_{SMU} + (1-(\text{SMU Fill Rate}))*\text{ACWT}_{WH}$$

(5) Crystal Ball® Random Variable Generator. This field requires the use of Crystal Ball® Monte Carlo simulation software to generate a fluctuating value for CWT in each step of the simulation. Again we attempted to use goodness of fit statistics to apply to all CWT values; however, no distributions suitably fit the CWT values across the NSNs that had more than 30 document numbers associated with them. While the lognormal distribution was often determined to be the best fit of those tested, no distributions were considered reliable fits. Therefore, we choose to apply the exponential distribution to the CWT, because it serves as a more conservative measure by overstating CWT values. The parameter for the exponential distribution is the reciprocal of the average CWT. Once completed, we repeated this process for each of the 202 NSNs in our study. At each iteration in our simulation, each cell (one for each NSN) randomly generates a CWT based on the exponential distribution for that NSN. When the same NSN is selected for more than one AAV during one iteration Crystal Ball® returns a discrete CWT value for each simulated requisition of that NSN that is based on the exponential distribution.

e. MTTR + ADT Add In

This field is created to add in the MTTR + ADT as computed for the model. This random variable is applied to each AAV that fails in our simulation. Based on another *IF* function, Excel will input the MTTR+ADT value into this field if the AAV in this row was simulated as deadlined.

f. Days Available/Days Deadlined

The next two columns list the number of days the asset was available and/or deadlined. If the asset was deadlined during the month, we simply subtract the MDT from 30 to find the needed value for the number of days available. On the other hand, if the item is not deadlined during one step in the simulation, then it was available for the entire month, or 30 days. This means that the item was available 100% of the month for use.

g. Calculated A_o

The next step was to simply calculate A_o. Within the model we used the following modified equation to compute the A_o during one simulation:

$$A_o = \frac{\textit{Total Time Available - Deadline Downtime}}{\textit{Total Time Available}}$$

Since our model uses a one-month period for each simulation step, our A_o equation is:

$$A_o = \frac{(30 - \textit{Days Deadlined})}{30}$$

This equation allows us to simulate A_o in relation to time. The current readiness reported rates for the Marine Corps are snapshots in time that state the current fully mission capable (FMC) status at a particular point in time, whereas A_o considers the entire time an asset is available. We thus created columns for both readiness and A_o. By dividing the number of days an asset was deadlined by 30, we determined the percentage of a month that an asset was mission capable in the readiness column. The mean of a measure of readiness over time is, in effect, the same as average A_o.

One issue that we had to address is that this model appears to assume that all assets automatically return to full service at the end of the month. So, we had to make sure that we were properly accounting for those times when MDT exceeded 30 days. Since our simulation is based on A_o over a 30 day period, whenever days deadlined *exceeds* 30 days for a particular asset, A_o will be identified as negative. For instance, when the total days deadlined is 72 days, the model penalizes the A_o calculation by factoring in the additional downtime above 30 days. The total impact to A_o lasts for 2.4 months, which is represented by a negative A_o. A_o for the month in which the item was deadlined would have been 0%. Since A_o in the second month would also have been 0%, the equation provides a negative 100% availability along with a negative 40% to account for the 12 days of the third month. Thus, in our simulated month, A_o for this particular AAV is negative 140%. Table 4 demonstrates a simulated step in the model, displaying two instances where MDT exceeded 30 days. Hence, although the model appears to

assume that all parts are working at the beginning of every month, the effect of down times longer than a month is properly captured.

Table 4. Simulated Month - A_o

Pool of AAVs	Failure?	CWT	MTTR+ADT	Days DL	Days Avail	A_o
1	0	0	0	0	30	100.00%
2	1	9	8	17	13	43.33%
3	1	14	8	22	8	26.67%
4	0	0	0	0	30	100.00%
5	0	0	0	0	30	100.00%
6	1	20	8	28	2	6.67%
7	0	0	0	0	30	100.00%
8	0	0	0	0	30	100.00%
9	0	0	0	0	30	100.00%
10	1	16	8	24	6	20.00%
11	0	0	0	0	30	100.00%
12	0	0	0	0	30	100.00%
13	0	0	0	0	30	100.00%
14	0	0	0	0	30	100.00%
15	1	64	8	72	-42	**-140.00%**
16	1	6	8	14	16	53.33%
17	0	0	0	0	30	100.00%
18	0	0	0	0	30	100.00%
19	1	25	8	33	-3	**-10.00%**
20	0	0	0	0	30	100.00%
21	0	0	0	0	30	100.00%
22	0	0	0	0	30	100.00%
23	0	0	0	0	30	100.00%
24	0	0	0	0	30	100.00%
25	0	0	0	0	30	100.00%
26	0	0	0	0	30	100.00%
27	0	0	0	0	30	100.00%
28	0	0	0	0	30	100.00%
29	1	12	8	20	10	33.33%
30	0	0	0	0	30	100.00%
… 216	1	11	8	19	11	36.67%
					One Month Simulated Ao =	**86.70%**

As our model simulates the A_o for each AAV, we applied the A_o equation to each end item row. To derive A_o across all 216 AAVs, we took the average of A_o from the entire fleet of vehicles to determine what A_o would be during one iteration of the simulation. The final step in completing this part of the simulation was to use Crystal Ball® to track the simulated A_o, and capture the distribution of this outcome variable.

We ran our model for 100,000 iterations, representing 100,000 simulated 30-day periods. This high number of iterations allows those NSNs with the lowest demand to be represented at least 30 times on average within each trial of our simulation. Crystal Ball® displays a probability distribution for results of the simulated A_o. Both the "As Is" simulation and the "To Be" simulation have forecasts defined in order to return a distribution for each scenario in order to measure the differences between the two. The "To Be" simulation scenario is discussed below.

3. Simulating the future ("To Be")

To properly simulate changes in A_o, we had to devise a method for simulating a scenario for what CWT would have been if the SMU had stocked the needed items. In order to do this, we found it necessary to establish the criteria for which items would be stocked based on CWT thresholds and build in service levels into the model that would incorporate a failure-based stocking methodology. A service level is defined as the percent chance that the SMU will not stock out during a given inventory cycle. This section discusses how we incorporated service levels into the model, what stock methodology was used for this model, and ultimately the impact the stock method and service levels have on CWT. All these variables can be modified in order to deliver results under various scenarios, other than the scenarios we examine in this thesis. In other words, the tool we have developed can be used for 'what-if' analysis on other scenarios. These methods are at the heart of what makes this model work.

a. CWT Threshold

The model provides a cell (input parameter) that allows the user to input any value for the average CWT that is desired: a 'threshold.' The value that is placed in this cell identifies those NSNs from our data set with average CWT above the threshold

and select them as candidates for moving forward in the supply chain. The data set is arranged so that any SECREP that would be a candidate is not moved forward because (as previously explained) SECREPs are outside the scope of this analysis.

In establishing these thresholds, we can incorporate new CWTs for those repair parts with lead times longer than our established thresholds. The first determinant factor is identifying the CWT that is too long, or unacceptable. If CWT is determined to be too long, then we must determine how much to stock at the SMU (forward positioned) in order to ensure these parts are delivered with the reduced CWT.

b. Model Stock Determination

Our model does not seek to determine optimal stocking criteria for the SMU; however, in order to demonstrate improvements in A_o and determine a quantifiable relationship between CWT and A_o in monetary terms (i.e., in order to know how much our recommendations would cost to implement), we had to apply a stocking methodology for the SMU. Due to the variability in both demand and lead time we chose the Re-Order Point (ROP) stock determination model. Within our model, the ROP stock method determines the appropriate stocking levels by applying a user-selected service level with the historical demand pattern for critical repair parts from 2009 to 2011. ROP must also be accompanied by an Economic Order Quantity (EOQ); however, optimal order quantities are not addressed in this paper and we assume that as an order is placed by the customer and fulfilled, an order for replenishment must also be placed by the SMU. The formula used to determine ROP in the model is as follows:

$$ROP = D * CWT + Z * \sigma_{ltd}$$

where:

D = Average daily demand

CWT = Lead time in days

Z = Number of standard deviations above the mean

σ_{ltd} = Standard deviation of lead time demand

To identify a stocking quantity, we determined safety stock requirements in addition to demand during the CWT period. Safety stock is determined by multiplying the *Z* score by the standard deviation of demand during lead time (CWT). A *Z* score value identifies the number of standard deviations an occurrence is from the mean. The *Z* score relates to the service level by indicating the corresponding point on the X-axis on the tail of a distribution curve. To obtain a *Z* score, we used the Excel function of NORMSINV(service level). Of course, use of a Z score assumes that demand during lead time follows a Normal distribution, a frequently used approximation, and we see no reason why it should be controversial. As service level increases, the *Z* score will also increase. The determination of values for our model was relatively straight forward, but to ensure that our model took variation in both demand and lead time we applied the following equation for σ_{ltd}:

$$\sigma_{ltd} = \sqrt{D^2\sigma_l^2 + L\sigma_d^2}$$

where:

D = Average daily demand

$\sigma_l =$ Standard deviation of CWT

L = Average CWT

$\sigma_d =$ Standard deviation of daily demand

c. Service Level to Fill Rate Conversion

The method we propose to decrease CWT is to pre-position critical repair parts forward in the supply chain, hence increasing safety stock levels at the intermediate supply activity to ensure those critical repair parts are readily available when they are needed. To gain a true picture of system wide wait time it is necessary to consider the delivery capabilities of the intermediate and wholesale supply activities within the supply chain. Intermediate supply activities do not make, or set, the stocking criteria at the wholesale supply level, and consequently when they experiences a stock out, their customers are subject to the delivery capabilities of the wholesale network. The charge for the SMU is to buffer the MEF against unacceptable lead times. This applies to both

CONUS and OCONUS operations, and when done correctly is a key component of mission success. Changes to the type and quantities of items stocked at the intermediate supply activity is one action that can be taken within a supply chain to reduce MDT while long term can be implemented.

As mentioned, this analysis of improving availability of readiness drivers does not provide an optimal stocking methodology for the SMU; however, by applying the ROP stock methodology we have created a model that is sensitive to service level changes to illustrate the impact of those changes on A_o. Service level is the probability that the SMU does not stock out during a cycle. Higher service levels result in higher fill rates, which will aid in buffering the impact of unacceptable CWT levels at the wholesale supply activities. Fill rates are not exactly the same as service levels. The fill rate from the SMU tells us the percentage of demand fulfilled from SMU stock.

Having a model that uses service level to determine the appropriate stock level at the SMU creates an interesting dilemma, as DoD reports performance based on fill rates. To align our research with this standard and to derive accurate A_o calculations, our "As Is" and "To Be" models were also built to incorporate fill rates into their calculations. The "As Is" model uses the actual data between 2009 and 2011 to form the consolidated CWT based on the fill rate of those NSNs over that period. Where the "To Be" model differs is in its application, which delivers a more accurate forecasted A_o calculation. The "To Be" model assumes that at higher service levels, the SMU can deliver according to their optimal delivery capabilities. Since our model uses fill rates to weight the CWT experienced from both the intermediate and wholesale supply levels, the optimal delivery capabilities of the SMU will decrease CWT that will result in benefits to A_o. Therefore, we converted the service level used in our ROP stock determination to a fill rate in order calculate forecasted A_o.

To determine what fill rate is experienced from a particular service level, we had to determine the percentage of stock outs that are expected per cycle and compare that number to demand over lead time. In the process of determining fill rate, all terms were converted into daily terms in order to correspond to the CWT measurement that is in days. There are two critical components to finding the number of expected stock outs,

which are the standard deviation of lead-time demand and the standard normal loss function. The standard deviation of lead time demand for service level to fill rate conversion is the same as discussed in the model stock determination method above. The equation for finding the number of expected stock outs per cycle is as follows:

$$N(R) = L(z)\sigma_{ltd}$$

where:

N(R) = The number of expected stock outs

L(z) = The standard normal loss function

σ_{ltd} = The standard deviation of lead time demand

The standard normal loss function represents what the expected value of losses will be, given that we experience a loss. The expected value of our loss is driven by the *Z* value that our stock method is based on. Selection of a desired service level as an input to the model provides a *Z* score. Anytime the input for service level is changed, the *Z* score in the model will update. Using the *Z* score, we can formulate a loss function that provides us with a conditional expectation of stock outs. To derive the standard normal loss function we use the following equation:

$$L(z) = NORMDIST(z, 0, 1, FALSE) - z * (NORMSDIST(-z)))$$

Once the standard deviation of lead-time demand and standard normal loss function have been computed, the number of expected stock outs per cycle can be calculated. By multiplying the standard deviation of lead time demand by the loss function, or *L(z)*, the number of expected stock outs per cycle is determined. The fraction of requisitions that are not filled is then derived by dividing the number of expected shortages per cycle by the expected demand during lead time. This fraction is then subtracted from 1 to provide the “To Be” fill rate. This allows the model to confirm that as service levels increase, the quantity to be stocked increases. As a result, the number of expected stock outs decreases and thereby increases the fill rate.

$$\text{Fill Rate} = 1 - \frac{N(R)}{D * L}$$

Figure 1 is a notional chart that depicts a service level with safety stock comprising Point X to Point Y, with Point X representing average expected demand. The probability of a stock out is represented by the area under the curve that is greater than point Y. Higher service levels will result in the requirement to increase safety stock to increase the probability that demand is met. This depicts the impact that service level has on inventory levels, and is at the heart of determining the fill rate discussed above.

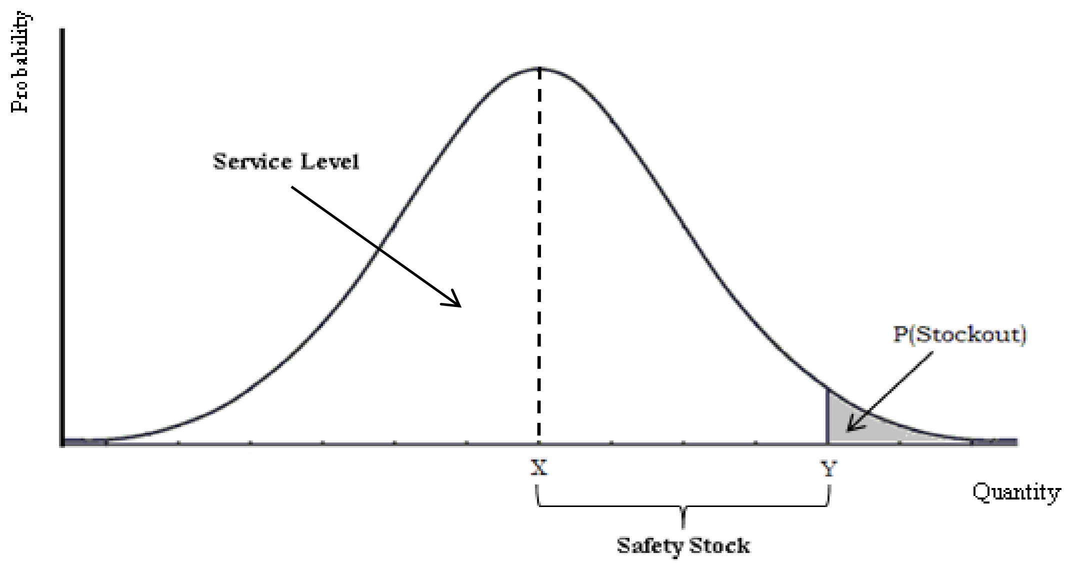

Figure 1. Probability of Stock Out

d. New System CWT Metrics for the "To Be" model

The final step in simulating the "To Be" conditions of the model is to use the new fill rate to determine what CWT would be under these altered conditions. When fill rates are set at different thresholds, then "To Be" CWT is derived using these new metrics in the same fashion as was described under section B.2.d *Consolidated CWT "As Is"* of this chapter. While the methods are the same, the data sources are different. The new weighted average for our scenario is derived from the new fill rate, and pulls its CWT data from Birdtrack's wholesale CWT data and SMU delivery times under ideal conditions. For those items that the model selects to be pre-positioned at the SMU under

our “To Be” analysis, the CWT for those items from the SMU is changed to 2.67 which is the average CWT experienced by the SMU when backorders are removed. This average is consolidated with the CWT from DLA and modeled as an exponential random variable to account for deviations in delivery to units aboard Marine Corps Air Station, Yuma, Arizona and the Marine Air Ground Combat Center in Twenty-nine Palms, California. We selected these values based on data received from the I MEF SMU in Camp Pendleton. We included this data as an input for the “To Be” conditions in the model that can be adjusted based on the time it takes for the intermediate supply activity to deliver to their customer.

Another area where the “To Be” differs from the “As Is” model is that not all NSNs are impacted by our stocking methods. Based on the threshold for moving items forward, the fill rate, ACWT, and StDev of CWT for the new model were left unchanged for items that did not meet the criteria for forward positioning. This applies to items like SECREPS, which are left unchanged in our study, as well as any NSN that has a CWT threshold less than the threshold set during the input process.

4. Model Outputs

In addition to simulated A_o and readiness for both the “To Be” and “As Is” scenarios, there are four additional outputs required to fully measure the benefit of forward stock positioning. These outputs include the number of FMC systems under both conditions, how many NSNs are impacted by our stock methods, how much money is required in total outlay, and how much of our recommended addition to forward-positioned inventory is at risk of *not* being used. These variables provide a final dimension whereby we can measure the cost of CWT reductions. Once the cost of our material stock decision is realized, measuring the impact our investments will have on A_o becomes more apparent.

a. Mission Capable Systems “As Is” and “To Be”

The first output we built into the model was a measure of the total FMC systems expected under both the “As Is” and “To Be” conditions. To derive this information, we multiplied the A_o during one month by 216 to return the total number of

expected AAVs available during that month. Using Monte Carlo simulation we can determine not only the average number of FMC systems, but the probability distribution of likely outcomes for FMC systems. These distributions can be used to answer post-hoc analysis questions such as “How likely is it we will have at least 185 mission capable AAVs?” The distributions are generated for both the “As Is” and “To Be” alternatives, so that they can be compared on the basis of risk, and not just average performance.

b. NSNs Moved Forward

The second additional input we needed was the number of NSNs impacted by our CWT threshold. The model sums the total number of NSNs that are candidates for pre-positioning and displays the information in the output section.

c. Total Outlay

To place this relationship in monetary terms, we must first identify the investment required to stock those NSNs that are pre-positioned in terms of total outlays. As discussed previously, the desired service level will determine the quantity of each NSN that requires investment. Intuitively, lowering CWT at various thresholds and/or raising the service level results in varying levels of additional investment. Modifications of these variables will demonstrate the relationship under our “To Be” analysis. Total investment outlay is determined by taking the unit price and multiplying the desired quantity stocked, as in the following equation:

$$K_i = UP\$ * n_i$$

where

K_i = Total outlay of NSN_i purchased if CWT threshold is exceeded

$UP\$_i$ = Unit Price of NSN_i

n_i = Recommended SMU stocking level for NSN_i

d. *Monetizing the Relationship between CWT and A_o with CIVaR*

Total outlay paints the picture for the one-time cost of our stocking methodology, but does not account for the likelihood that what we stock will be ordered. What is or is not ordered is important because when items are ordered, the SMU is reimbursed for the item by the unit ordering it. To fully grasp the relationship between CWT and A_o, we must determine the cost of reducing A_o, and thus monetize the relationship. There are two general components to the ROP-based stocking method recommended in this study: the cycle stock and safety stock. On average, the SMU assumes the entirety of risk associated with the safety stock they hold, because it is above and beyond the average number of expected items demanded. Cycle stock, however, is expected to be used but has the potential of not being used based on fluctuations in demand. If these critical repair parts are projected to be ordered sometime throughout the fiscal year, then there is limited budgetary concern for that fiscal year.

It is important to know the likelihood that SMU-stocked items will not be used, because this provides a true measure of what the real cost our stock method has due to uncertainty. When an item is stocked at the supply activity (e.g., SMU) but not used, then the supply activity is penalized for the overage. This overage is essentially the holding costs and opportunity costs of money that was tied up in excess inventory. To compute the penalty for items that may not be demanded, we use a variant of the conditional value-at-risk (CVaR) metric proposed by Rockafellar & Uryasev (2000). For the purpose of this study, we call this the conditional inventory value-at-risk (CIVaR) and it will show the true cost of our material stock decisions based on risk. Within our analysis, the CIVaR will include the safety stock and the cycle stock needed to achieve various service levels and reduce CWT. This study serves to identify the potential penalty of inventory cost in nominal dollar terms for safety stock and cycle stock, but does not identify ongoing holding costs or the SMU's opportunity costs of using those funds for other purchases. In other words, we are providing an approximate measure of the budget impact to the SMU, assuming they currently carry no local stock of the item. We are not attempting to measure the incremental cost, because that would require a detailed

knowledge of the current stocking methodology, and a prescription for the "To Be" stocking methodology.

To determine the probability of demand for repair parts at various quantities, we had to apply a distribution to demand. The Poisson distribution can be applied when occurrences are independent of each other and the average number of occurrences for a given time period is known (Hu, 2008). Demand for repair parts meets the Poisson distribution requirements, and thereby it was chosen as the distribution of future demand in our model. Using the Poisson distribution we computed the average demand during lead time which serves as the mean in our CIVaR calculation. The model uses the probabilities that demand equals incremental values during lead time to calculate CIVaR. Thus, the model calculates CIVaR for those items chosen as candidates for forward positioning at the SMU.

We used the Excel "Poisson" function to determine the probability that demand will be less than the "To Be" stocking level (in which case, the extra stock would be excess). The CIVaR is calculated for each incremental occurrence of possible demand below our stocking level by first multiplying the probability that demand is equal to a value *X* by the difference between the recommended stock and demand *x* by the unit price of the NSN. Then, the sum of each incremental value *x* gives us the CIVaR. The equation used to calculate the CIVaR is derived as follows:

$$\text{Conditional Inventory Value at Risk (CIVaR)} = \sum_{x=0}^{N_t} P(X = x) * (N_t - x) * (UP\$)$$

where

N_t = "To Be" stocking level

X = Projected value of actual future demand during lead time

x = Target value of demand during lead time

UP$ = Unit price of the NSN selected

An example of the CIVaR concept is graphically depicted in Figure 2. Based on the assumption of Poisson demand, the average quantity demanded is 5 for this notional NSN. At the 90% service level, the ROP stocking methodology recommends a

notional stocking posture of 8. The shaded area represents the probability that demand is between 0 and 8. The CIVaR will be equal to the sum of the probability at each value from 0 to 8 multiplied by the difference between the stock quantity and each potential demand value from 0 to 8 multiplied by the unit price of this notional NSN.

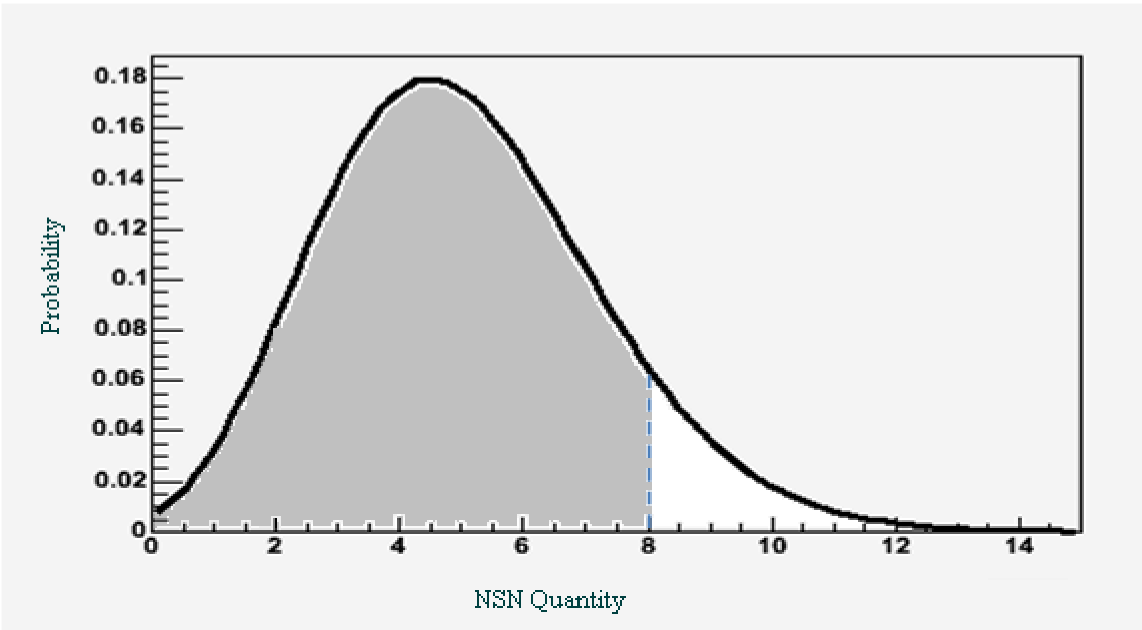

Figure 2. Notional CIVaR Depiction

Equally important to how the model calculates CIVaR is its relationship with total outlay. The CIVaR changes as service levels and CWT thresholds are modified since stocking levels correspondingly change. The model also simulates the impact of these changes by dividing the CIVaR by total outlay, which tells us the percent of our investment that is at risk of not being used. Intuitively, as service levels are increased so does the CIVaR.

C. MODEL VALIDATION

The model described above is designed to show the impact of reductions in CWT on A_o, and it accomplishes that task by comparing the operating conditions of the past with an alternative stock policy. With this in mind and before the model could be used,

the first step was to validate the simulated “As Is” scenario comparing it with the historical readiness data. To make our comparison, we looked at the historical LM2 Unit Report data that identified readiness rates on a weekly basis from 2009 – 2011. We then conducted simulations using Crystal Ball (100,000 trials) which created the “As Is” simulation A_o and readiness data. A comparison of the results of our simulation and the actual readiness rates are in Table 5.

Table 5. Comparison of Actual and Simulated Readiness I MEF, 2009–2011

TAMCN	Nomenclature	Avg # of Assets	Avg R% (historical)	σ of R% (historical)	Avg R% (simulated)	σ of R% (simulated)
E0846	Assault Amphibious Vehicle, Personnel AAVP7A1	216	87.39%	5.23%	86.55 %	5.8%

While the historical readiness mean and standard deviation are similar to the “As Is” simulated readiness mean and standard deviation, we further validate the model by examining the entire distribution of A_o. To accomplish this, we examined our simulated results using the method that the Marine Corps uses to report readiness levels. Marine Corps Order 3000.13, *Marine Corps Readiness Reporting Standard Operating Procedures*, directs that units report their readiness information monthly via DRRS. The criteria set forth by this directive are as follows:

R1 – R $\geq$ 90%

R2 – 70% $\leq$ R $\leq$ 89%

R3 – 60% $\leq$ R $\leq$ 69%

R4 – R < 60%

These levels indicate that if a unit’s equipment readiness is above 90%, that unit will have a R1 rating. If the unit’s equipment readiness is above 70% and below 90%, that unit will have a R2 rating, and so forth. Referring to our historical readiness data, the tails of that distribution revealed that under current operating conditions 34.6% of the R

values were in R1, 65.4% in R2, 0% in R3, and 0% in R4. Our simulation of 100,000 iterations revealed that the data under continuous use falls out in a similar fashion with 30.6% of all observances occurring on R1, 67.9% in R2, 1.3% in R3, and 0.2% in R4. This data is presented in Table 6.

Table 6. Historical and Simulated Readiness DRRS Comparisons

Threshold Level	Historical Readiness	Simulated Readiness
R1	34.6%	30.6%
R2	65.4%	67.9%
R3	0%	1.3%
R4	0%	0.2%

The small disparities between the historical data and our simulation output support the validity of our model. Moreover, even these small disparities can be explained by the way that DoD uses equipment. Peltz et al. (2002) describes DoD equipment usage and demand for repair parts as being tied to unit operational commitments and training schedules. Hence, readiness rates are driven as a result of the operational tempo of the unit. According to operations and maintenance personnel at 3d AAV Battalion in Camp Pendleton, CA, the current operating tempo in CONUS for AAVs is a 3:1 ratio between field training and garrison usage. In other terms, the battalion conducts field exercises during one week per month on average, which accounts for approximately 25% of a month. During field training, AAVs operate approximately 8–10 hours during the week on average. While in garrison, the AAVs are exercised approximately 1.5 hours per week. Thus, most failures result from heavier usage of the AAVs during 25% of the month.

As the AAVs are used during field training, failures result more often than when they are only minimally operated in a garrison environment. Therefore, demand for repair parts occurs at a higher rate near the end or after a field exercise. During limited operations in garrison, when preventive maintenance primarily occurs, demand for critical repair parts is diminished. The result is “lumpy” demand patterns. Although our

model demonstrates the effects on A_o over time, it assumes continuous use of assets. As a result, we expect to see fewer occurrences near the 100% readiness level and subsequently fewer occurrences above 90%, and ultimately a greater proportion of observations closer to the mean. In this manner, our model marginally overstates readiness risk of asset availability on the right side of the A_o distribution tail.

On the left side of the data we also observe more items reaching R3 and R4 in our simulation model than in the historical data. The lack of observations in the historical data in the R3 and R4 thresholds is indicative of maintenance actions taken outside of the normal supply channels, known as workarounds. These workarounds are actions such as selective interchange and part swapping between units that allow the maintainer to repair equipment without having to wait for supply support. However, our model marginally understates readiness risk on the left side of the distribution's tail. Because of this underestimation, we do not expect improvements to A_o or changes throughout the distribution to be directly derived from the difference between the historical conditions and the model outputs. The benefits of this model will instead be measured based on the changes seen between the "As Is" and "To Be" simulation outputs.

Based on the similarities in the historical data and our simulated "As Is" data, we conclude that our model has high fidelity in capturing the relationship between A_o and CWT. We believe that our model is valid for demonstrating the effects on A_o as we make changes to CWT for critical repair parts. There is no reason to believe that the distribution of the actual data and the simulation are different, but this cannot be validated without an operational test. When conducting our "To Be" analysis, we must consider these biases as we compare results and present them for advice in decision making.

V. ANALYSIS & RESULTS

In the Methodology chapter, we provided a means of simulating A_o based on historical CWT and failure data. Within these simulations, adjustments can be made to the input variables in the model that will provide different scenarios in the “To Be” portion of the model. The model is versatile in its capability of comparing the “To Be” A_o with the “As Is” scenario to show the benefit of various material stock decisions based on changes in the input criteria. This model bridges the gap found by the RAND Corporation, the DoD Inspector General, and other DoD agencies looking to quantify the impact of material decision on A_o by narrowing the focus to one end item down one supply chain. This model then serves as a decision tool to aid leaders in making stock decisions based on both cost and benefit. The analysis is designed to answer the remaining research questions:

1) What CWT thresholds should we examine for target reduction?
2) What should our desired service level be for part stocking criteria?
3) What is the likely return (in terms of A_o) on our investment in CWT, and what is the riskiness of that return on investment?

To answer these research questions it was necessary to alter the “To Be” CWT data experienced in the system to that of the conditions the SMU experiences under optimal conditions. Our analysis begins with testing the model’s impact on A_o at various inputs for both Service Level and CWT thresholds. In addition to improvements in A_o, Monte Carlo simulation reveals that there are benefits found throughout the distribution of A_o, such as in improvements in DRRS-MC reporting categories. The distributional benefit requires further discussion, and reveals that material stock decisions serve to not only improve upon the average, but they improve upon our readiness risk. Having explored the benefits, we then discuss the total investment at risk, which demonstrates to decision makers the costs of various material stocking options. Lastly, we look at the limitations of this model, and discuss the relevance of our model under these conditions.

A. CWT THRESHOLDS AND SERVICE LEVEL ANALYSIS

The objective of this research is to use simulation modeling to show the impact that CWT reductions (via various material stock decisions) have on A_o. The model produces results based on the desired service level and CWT threshold inputs. To test the possible outcomes, we ran simulations of the model based on the service levels of 0.8, 0.9, 0.95, 0.99 with CWT thresholds of 30, 20, 15, and 10 days in a 4x4 factorial design. That is, we simulated all 16 scenarios resulting from the combinations of four service levels with four CWT thresholds. These levels represent a range of acceptable service levels and CWT thresholds. We did not specifically test for interaction (that is, we did not test to see if simultaneous changes to CWT threshold and service level had a multiplicative effect), although the Ao results would incorporate any interactive effect (implicitly in the simulation).

As we ran the model using these possible scenarios, we found significant and quantifiable improvements to average A_o. Table 7 illustrates how A_o responds to CWT-based material stock decisions.

Table 7. Impacts on A_o at Various SLs and CWT Thresholds

Observed A_o (Mean, StDev, 100,000 trials): CWT and Service Level Martrix								
"As Is" A_o: 86.54%, StDev: 5.81%								
	CWT > 30		CWT > 20		CWT > 15		CWT > 10	
Result Cells:	A_o	StDev	A_o	StDev	A_o	StDev	A_o	StDev
SL - 0.80	87.41%	5.52%	87.48%	5.51%	87.81%	5.48%	88.37%	5.46%
SL - 0.90	87.62%	5.51%	87.74%	5.51%	88.14%	5.50%	89.02%	5.44%
SL - 0.95	87.68%	5.55%	87.85%	5.54%	88.35%	5.48%	89.27%	5.41%
SL - 0.99	87.76%	5.53%	87.93%	5.51%	88.43%	5.49%	89.43%	5.39%
NSN - MOVED FORWARD	25		38		59		106	

When comparing the model results to our simulated "As Is" A_o of 86.54% against a policy that sets a .80 service level with a CWT threshold of 30 days, the model recommends that we alter our stock methodology for 25 NSNs, and that we can expect a 1.07% improvement to A_o. On the other end of that spectrum, at the .99 service level, when the CWT threshold is set to move forward all items that have a CWT greater than

10 days, the model recommends to alter the stock method for 106 NSNs and provides that we can expect an improvement of nearly 3% to A_o. The difference between 1 and 3 percent when put in terms of weapons systems is quite significant. What these numbers actually represent is the addition of between 2.16 and 6.48 additional FMC systems on average. In the case of an AAV battalion, this represents the ability to get an additional 42 or 126 Marines into the fight.

Figure 3 demonstrates the impact that various service levels have on A_o based on a 10-day CWT threshold.

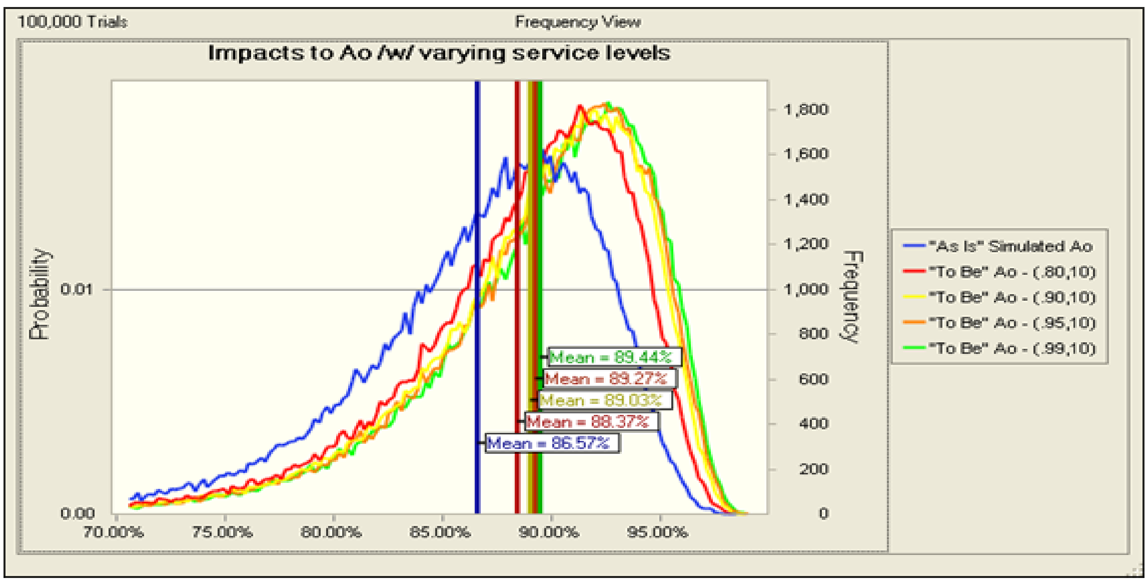

Figure 3. Impacts to A_o at 10-day CWT Threshold and Various SLs

When increasing service levels, we intuitively expect the mean to move up significantly, but there is actually little impact to A_o. CWT threshold, on the other hand, appears to have a more significant impact on A_o. Using the .90 SL, Figure 4 displays how A_o improves with each CWT threshold reduction.

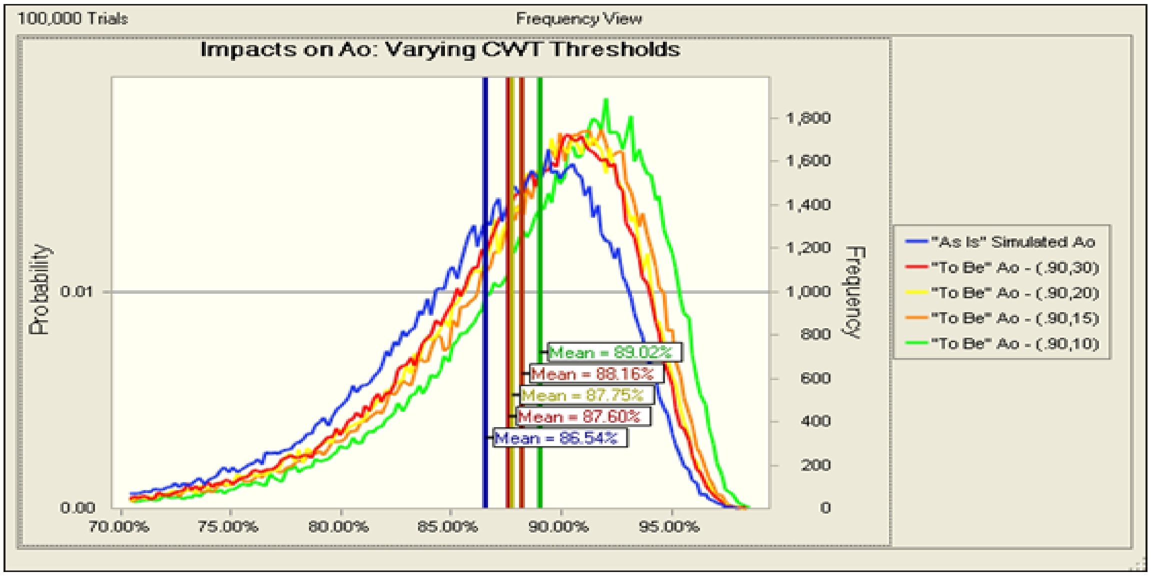

Figure 4. Impacts to A_o at .90 SL and Various CWT Thresholds

Figures 3 and 4 demonstrate that the very act of targeting critical NSNs for CWT reduction results in significant gains to A_o. As we throw more and more material at the problem we find that the gains are marginally increasing, but there is another benefit that must be analyzed before we can capture the complete benefits of forward positioning stock. This turns our analysis from changes in the average A_o to identifying how much risk can be reduced through material stocking decisions.

B. REDUCTION OF READINESS RISK

According to Kang, Doerr, and Sanchez (2006) and Kang, Doerr, Apte, and Boudreau (2010), readiness risk measures the probability that A_o will fall below, or between, identified ranges. In addition to being able to measure the benefit to improvements in the average A_o, Crystal Ball's Monte Carlo simulation software allows us to dissect the distribution of A_o. Using Crystal Ball to analyze the simulated distribution allows us to measure differences in A_o at various ranges in the distribution, which lends to the quantification of readiness risk. This analysis will compare readiness risk between the "As Is" and the "To Be" scenarios to derive an expected benefit.

Crystal Ball® allowed us to track the observations of the data based upon their likelihood of occurrence. For example, when using inputs of a service level of .9 and

CWT threshold of 10, Crystal Ball allowed us to estimate the probability of A_o falling below 85%, as shown by Figure 5.

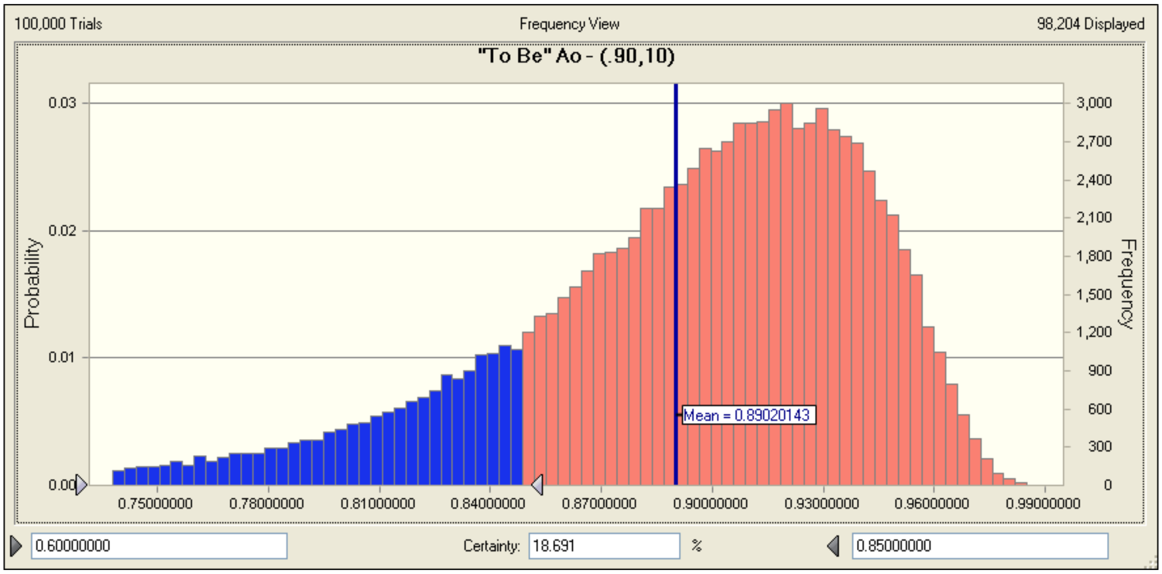

Figure 5. Probability of A_o below 85% (.90 SL and 10-day CWT Threshold)

This chart tells us that there is a 18.69% probability that A_o will be below 85% under these conditions. This is compared to the 32.37% probability that A_o falls below 85% in the "As Is" simulation, as depicted in Figure 6.

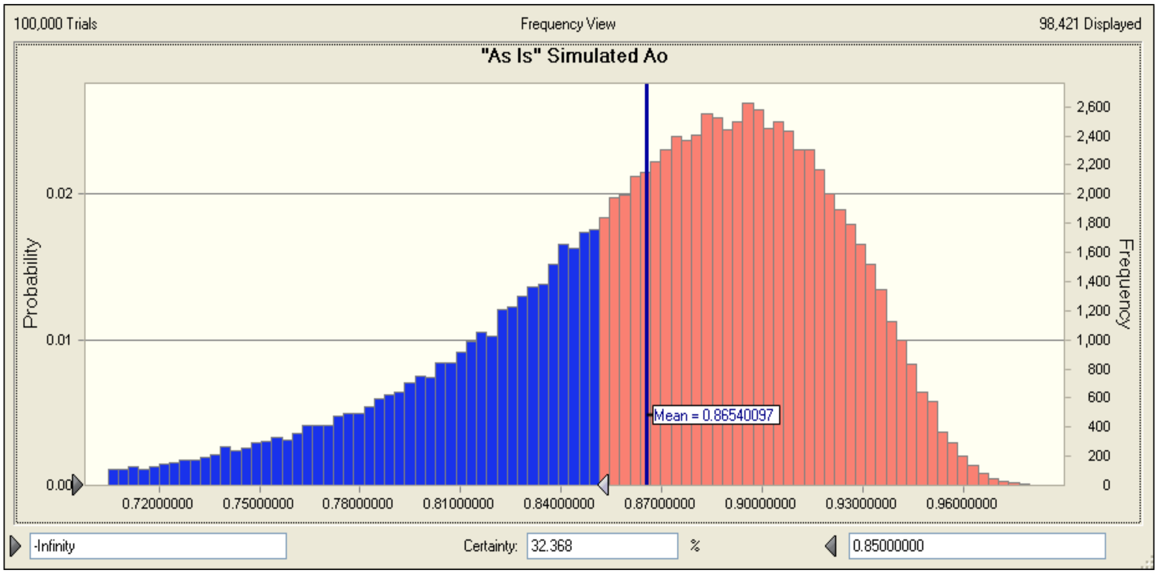

Figure 6. Probability of A_o below 85% ("As Is" Simulation)

In addition to the left tail of the distribution, we can look at how the distribution shifts by setting the lower bound to .9 without an upper bound to show the probability of A_o occurring above 90% as shown in Figure 7.

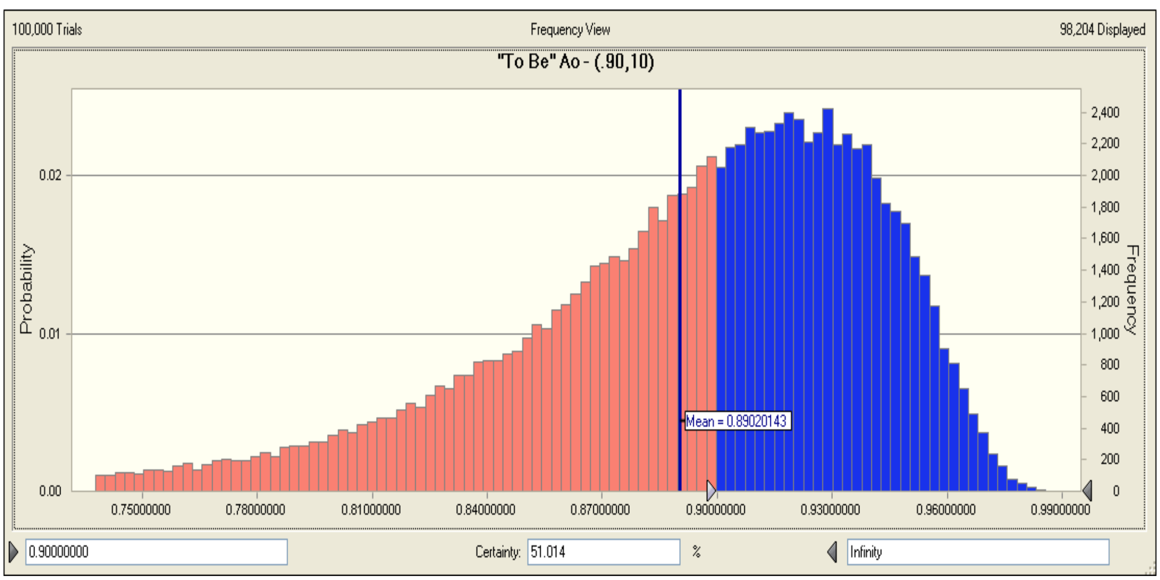

Figure 7. Probability of A_o above 90% (.90 SL and 10-day CWT Threshold)

Focusing on the right tail allows decision makers to measure the probability of readiness falling within the R1 threshold of DRRS-MC. Additionally, when missions dictate that a minimum level of readiness or a minimum number of FMC systems is required, the model can provide a forecasted probability of attaining a desired goal. The information that Figure 7 reveals that we can be 51.01% certain that A_o will be above 90% in a given month.

Crystal Ball's frequency chart provides the means whereby the entirety of our simulated distribution can be sampled and measured against the base case to show the benefit of material stock decisions. To demonstrate the impact of readiness risk, we recorded the probability of A_o being lower than 85%, as well as the probability of A_o falling within the DRRS reporting R1, R2, R3, and R4 ranges. The results of this analysis are found in Table 8. These are quantile estimates provided by Crystal Ball® after a simulation run of 100,000 iterations. We did not seek to qualify these estimates in any way (for example, by building a confidence interval around the estimates), but simply present them as descriptive statistics.

Table 8. Impacts to DRRS-MC R-Levels at Various SLs and CWT Thresholds

CWT TH	SL	P(R < 85%)	DRRS R1	DRRS R2	DRRS R3	DRRS R4
30	0.80	26.64%	36.79%	62.08%	0.99%	0.14%
30	0.90	25.45%	38.66%	60.27%	0.93%	0.15%
30	0.95	25.06%	39.40%	59.54%	0.91%	0.15%
30	0.99	24.66%	40.03%	58.92%	0.89%	0.16%
20	0.80	26.29%	37.68%	61.20%	0.98%	0.14%
20	0.90	24.89%	39.83%	59.14%	0.91%	0.12%
20	0.95	24.27%	41.07%	57.87%	0.93%	0.14%
20	0.99	23.87%	41.68%	57.29%	0.92%	0.12%
15	0.80	24.41%	40.37%	58.60%	0.92%	0.12%
15	0.90	22.83%	43.43%	55.58%	0.88%	0.12%
15	0.95	21.72%	45.41%	53.64%	0.83%	0.12%
15	0.99	21.46%	46.17%	52.95%	0.77%	0.11%
10	0.80	21.79%	45.53%	53.59%	0.78%	0.11%
10	0.90	18.79%	51.01%	48.18%	0.71%	0.10%
10	0.95	17.18%	53.30%	45.96%	0.66%	0.09%
10	0.99	17.35%	54.54%	44.76%	0.61%	0.09%

Figure 8 further demonstrates the reduction of risk in terms of the probability of A_o occurring below 85% at various CWT thresholds and service levels.

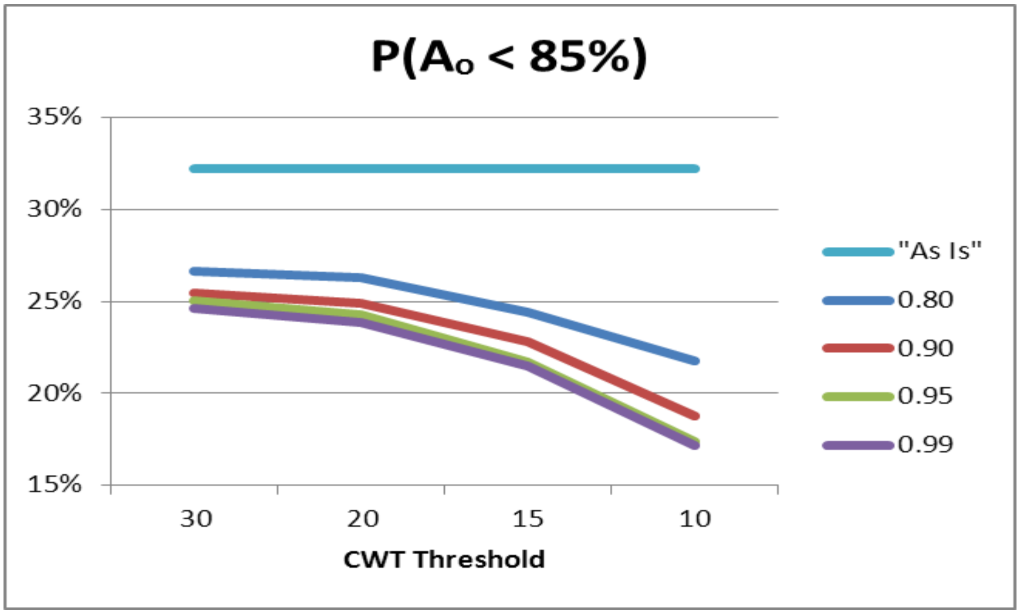

Figure 8. Probability of A_o below 85% at Various SLs and CWT Thresholds

Within the confines of financial capability, this model provides a means whereby decision makers can choose an option based on service level and CWT threshold that best meets the operational requirements of the future. The benefits of reducing CWT must include both measurements of the average and the distributional gains related to those decisions. This type of analysis makes the benefit of reductions in CWT easy to understand, but we must also address the monetary implications of material stock decisions. Seeking the most value for the investment should drive DoD's material stock decisions, and due to funding constraints there are always points where cost outweighs the benefit. This model does not identify these points where cost outweighs benefit, but instead provides a tool for decision makers to determine the value of improvements to A_o and risk reduction.

C. INVESTMENT RISK ANALYSIS

A true cost analysis of our model's recommendation from the Navy's perspective would require examining the cost of holding stock (at all echelons) against the cost of deadlining events (somehow monetized). This is clearly beyond the scope of this thesis.

Instead, as we have done with our analysis of A_o and CWT, we maintain our perspective at the SMU level. Even here, we cannot really calculate the incremental cost of our policies, because we do not have the data (current stocking levels and policies) to calculate the cost of the status quo, and hence, cannot calculate the incremental costs of the changes we are recommending.

However, we can provide a limited estimate of the one-time budgetary impact of our recommendations on the SMU. There are two financial measures used in this research to show the budgetary impact of stock level decisions. The first of these is the total outlay, or the total cost of purchasing all material recommended by our model. However, estimating the budgetary impact on total outlay is inadequate, as there is a portion of the investment which will be used and thereby the SMU will be reimbursed for the cost of those items. The true budgetary impact to the SMU is the stock moved forward in the supply chain that is not used in the current budget year. In hindsight, this would seem to represent an unnecessary expenditure to the SMU in the current budget year. However, we cannot call this a cost, because the material will eventually be used, and the SMU will eventually be reimbursed (given that the items have sufficient shelf life and do not become obsolete). The point is that, in hindsight, the SMU did not need to expend the funds *this* year.

The CIVaR described in the methodology chapter provides an answer to how much our material stock decisions impact the budget. We understand that actual cost would also need to incorporate the savings from reductions in expedited part shipments; after all, the SMU can order its needed inventory at a lower priority and thereby forego expedited shipments, but for the purpose of this project we assume the shipping cost to be constant. Finally, note that since we do not know the current stocking allowances at the SMU, we cannot really be sure about the *incremental* expenditure required to raise

service levels or reduce CWT to the desired threshold. Hence our CIVaR estimates are best considered as upper bounds, or maximum additional expenditures required, rather than estimates of average expenditures required. The CIVaR associated with each service level and CWT threshold are provided in Table 9.

Table 9. CIVaR: CWT and Service Level Matrix

CIVaR: CWT and Service Level Matrix				
	CWT > 30	CWT > 20	CWT > 15	CWT > 10
Result Cells:				
SL - 0.80	$57,770	$61,104	$85,650	$138,018
SL - 0.90	$79,501	$83,124	$119,965	$192,978
SL - 0.95	$95,056	$99,860	$143,036	$232,277
SL - 0.99	$132,908	$138,133	$198,108	$319,002
NSN - MOVED FORWARD	25	38	59	106

Figure 9 graphically demonstrates the CIVaR at various CWT thresholds and service levels.

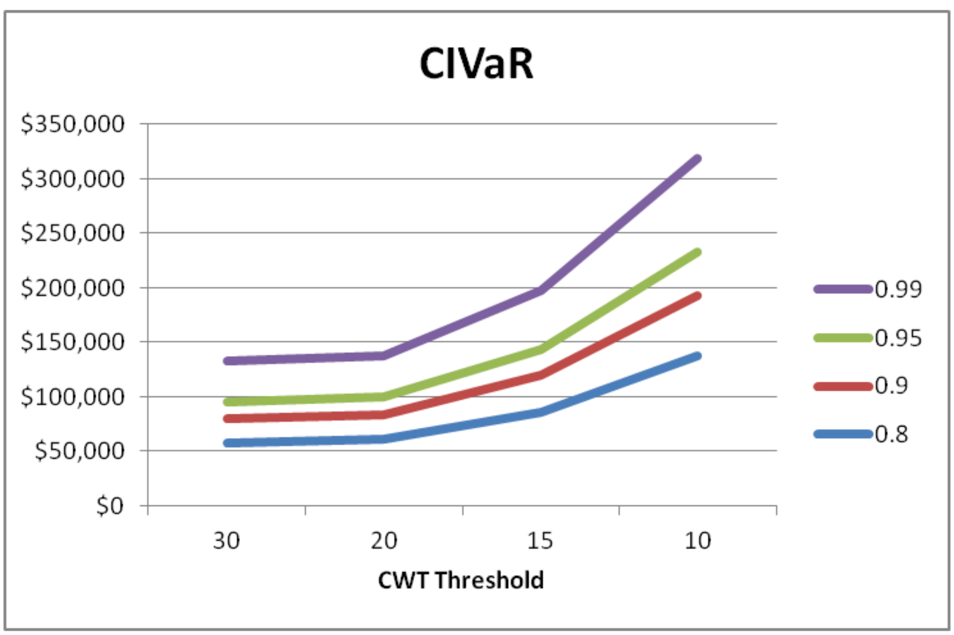

Figure 9. CIVaR Analysis

Intuitively as we increase the service level, the CIVaR also goes up. This is the inevitable result of increasing the amount of safety stock in the system as service levels rise. The CIVaR can then be used as the measurement of budgetary impact as compared to the benefit in A_o, and thus these results can be measured in terms of return on investment of the SMUs limited budgetary dollars.

We also examined our results in terms of the monetary relationship in terms of CIVaR and the resultant A_o. Figure 10 graphically depicts this relationship.

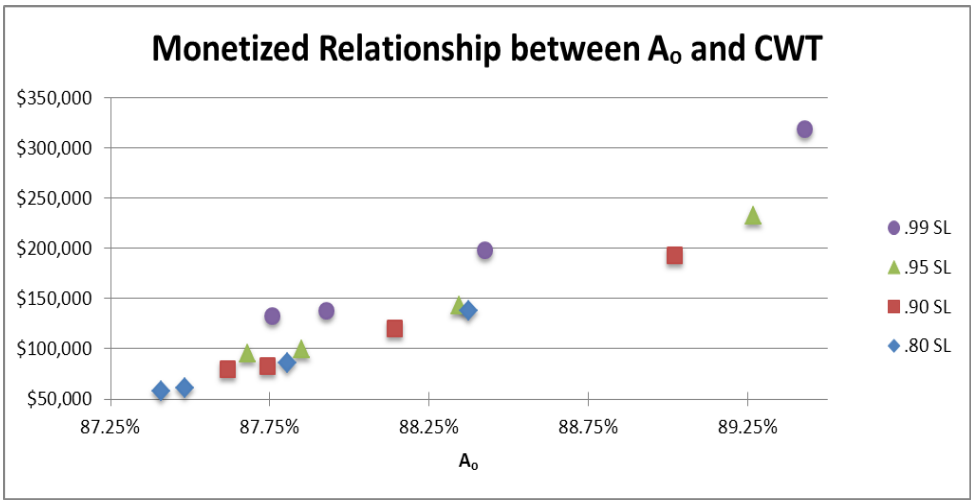

Figure 10. Monetized Relationship between A_o and CWT

This graph demonstrates the marginally exponential nature of a monetary solution, in terms of pre-positioning inventory in order to reduce CWT, and its subsequent impact upon improving A_o. As initial investments in pre-positioning inventory are made, substantial improvements to A_o result. As inventory investment continues to increase for additional NSNs representing additional CWT thresholds, we begin to see a diminishing benefit to A_o. Figure 10 can be used by decision makers to determine the most cost effective way to achieve a desired end state in terms of A_o.

In Table 7, we illustrated how increasing stock positions at the various CWT thresholds through an increase in service levels tends to increase A_o. Table 10 now illustrates the budgetary cost and benefit of material stock decisions at each CWT

threshold and Service level in terms of improved A_o, CIVaR, readiness risk, as well as from a mission capable unit basis.

Table 10. Cost / Benefit Matrix

CWT TH	SL	"To Be" Ao	CIVaR	P(R < 85%)	DRRS R1	BENEFIT (Ao)	FMC UNIT	CIVaR/UNIT
30	0.80	87.41%	$57,770	26.64%	36.79%	0.87%	1.88	$30,653
30	0.90	87.62%	$79,501	25.45%	38.66%	1.08%	2.33	$34,071
30	0.95	87.68%	$95,056	25.06%	39.40%	1.15%	2.47	$38,412
30	0.99	87.76%	$132,908	24.66%	40.03%	1.22%	2.64	$50,314
20	0.80	87.48%	$61,104	26.29%	37.68%	0.95%	2.05	$29,875
20	0.90	87.74%	$83,124	24.89%	39.83%	1.21%	2.61	$31,870
20	0.95	87.85%	$99,860	24.27%	41.07%	1.31%	2.84	$35,163
20	0.99	87.93%	$138,133	23.87%	41.68%	1.39%	3.01	$45,908
15	0.80	87.81%	$85,650	24.41%	40.37%	1.27%	2.74	$31,239
15	0.90	88.14%	$119,965	22.83%	43.43%	1.61%	3.47	$34,571
15	0.95	88.35%	$143,036	21.72%	45.41%	1.81%	3.91	$36,587
15	0.99	88.43%	$198,108	21.46%	46.17%	1.89%	4.08	$48,516
10	0.80	88.37%	$138,018	21.79%	45.53%	1.84%	3.97	$34,756
10	0.90	89.02%	$192,978	18.79%	51.01%	2.48%	5.37	$35,967
10	0.95	89.27%	$232,277	17.35%	53.30%	2.73%	5.90	$39,348
10	0.99	89.43%	$319,002	17.18%	54.54%	2.89%	6.25	$51,034

When we sort the data according to the number of additional FMC systems we can expect, the model is an excellent tool for the decision makers in regard to material stock decisions. In such cases when the required number of additional FMC systems is our metric, decision makers can select the option that provides that measure at the lowest cost. For example, assume that decision makers require 5 additional FMC AAVs above their current average number of FMC AAVs. Using the table above, they can simply scroll from the bottom to the top of the MC Unit Column until they find a scenario that provides the needed mission capable systems. If the end state is a system where we require 5 additional FMC systems, then the lowest cost solution is to stock based on a CWT threshold of 10 days at the .80 service level. This model provides a flexible system whereby stock decisions can be made based on the impact those stock decisions will have on the number of FMC systems.

Decision makers at the MEF or the SMU can use the CIVaR to measure how much of the stocking investment is at risk, which depicts the budgetary impact to them, in order to make a fully informed risk/reward decision. Additionally, this information can provide decision makers with the cost/benefit of CIVaR in relation to benefits in A_o as

well as the DRRS-MC R-rating levels. A complete account of all results of our simulation using all SLs and CWT thresholds is depicted in Table 11.

Table 11. Summary of A_o / CWT / CIVaR Analysis

SERVICE LEVEL .80	"AS IS"	CWT > 30	CWT > 20	CWT > 15	CWT > 10
A_o	86.54%	87.41%	87.48%	87.81%	88.37%
A_o - StDev	5.81%	5.52%	5.54%	5.48%	5.46%
% Chance A_o < 85%	32.23%	26.64%	26.29%	24.41%	21.79%
% Change		5.59%	5.94%	7.82%	10.44%
NSN - MOVED FORWARD		25	38	59	106
Total Outlay		$81,986	$85,728	$121,506	$193,423
Value at Risk		$57,770	$61,104	$85,650	$138,018
% AT RISK		70.46%	71.28%	70.49%	71.36%
R1 - R > 90%	30.60%	36.79%	37.68%	40.37%	45.53%
R2 - 70% < R < 90%	67.88%	62.08%	61.20%	58.60%	53.59%
R3 - 60% < R < 70%	1.31%	0.99%	0.98%	0.92%	0.78%
R4 - R < 60%	0.21%	0.14%	0.14%	0.12%	0.11%

SERVICE LEVEL .90	"AS IS"	CWT > 30	CWT > 20	CWT > 15	CWT > 10
A_o	86.54%	87.62%	87.74%	88.14%	89.02%
A_o - StDev	5.81%	5.51%	5.51%	5.50%	5.44%
% Chance A_o < 85%	32.23%	25.45%	24.89%	22.83%	18.79%
% Change		6.78%	7.34%	9.40%	13.44%
NSN - MOVED FORWARD		25	38	59	106
Total Outlay		$103,874	$107,905	$156,263	$248,906
Value at Risk		$79,501	$83,124	$119,965	$192,978
% AT RISK		76.54%	77.03%	76.77%	77.53%
R1 - R > 90%	30.60%	38.66%	39.83%	43.43%	51.01%
R2 - 70% < R < 90%	67.88%	60.27%	59.14%	55.58%	48.18%
R3 - 60% < R < 70%	1.31%	0.93%	0.91%	0.88%	0.71%
R4 - R < 60%	0.21%	0.15%	0.12%	0.12%	0.10%

SERVICE LEVEL .95	"AS IS"	CWT > 30	CWT > 20	CWT > 15	CWT > 10
A_o	86.54%	87.68%	87.85%	88.35%	89.27%
A_o - StDev	5.81%	5.55%	5.54%	5.48%	5.41%
% Chance A_o < 85%	32.23%	25.06%	24.27%	21.72%	17.35%
% Change		7.16%	7.96%	10.50%	14.88%
NSN - MOVED FORWARD		25	38	59	106
Total Outlay		$119,532	$124,752	$179,445	$288,326
Value at Risk		$95,056	$99,860	$143,036	$232,277
% AT RISK		79.52%	80.05%	79.71%	80.56%
R1 - R > 90%	30.60%	39.40%	41.07%	45.41%	53.30%
R2 - 70% < R < 90%	67.88%	59.54%	57.87%	53.64%	45.96%
R3 - 60% < R < 70%	1.31%	0.91%	0.93%	0.83%	0.66%
R4 - R < 60%	0.21%	0.15%	0.14%	0.12%	0.09%

SERVICE LEVEL .99	"AS IS"	CWT > 30	CWT > 20	CWT > 15	CWT > 10
A_o	86.54%	87.76%	87.93%	88.43%	89.43%
A_o - StDev	5.81%	5.53%	5.51%	5.49%	5.39%
% Chance A_o < 85%	32.23%	24.66%	23.87%	21.46%	17.18%
% Change		7.57%	8.36%	10.77%	15.05%
NSN - MOVED FORWARD		25	38	59	106
Total Outlay		$157,406	$163,047	$234,598	$375,137
Value at Risk		$132,908	$138,133	$198,108	$319,002
% AT RISK		84.44%	84.72%	84.45%	85.04%
R1 - R > 90%	30.60%	40.03%	41.68%	46.17%	54.54%
R2 - 70% < R < 90%	67.88%	58.92%	57.29%	52.95%	44.76%
R3 - 60% < R < 70%	1.31%	0.89%	0.92%	0.77%	0.61%
R4 - R < 60%	0.21%	0.16%	0.12%	0.11%	0.09%

D. LIMITATIONS OF THE MODEL

Our model involves looking to the past to forecast the future. Our analysis centered on the NSNs whose failures resulted in deadlining events. Based on the failure rates of these NSNs, we expect to see similar failures in the future, given the same operating conditions (operational tempo, operating climate, consistent maintenance personnel skill levels, etc.). If these factors change, then NSN failure rates will also change. Additionally, the model does not incorporate other NSNs that will potentially have future failures that our analysis did not capture based on historical failures. Better forecasting tools would ameliorate this problem, but the examination of forecasting tools is beyond the scope of this thesis.

The model does not incorporate the possibility of a single AAV failing, being returned to a mission capable status, and then followed by another failure all within the same simulated month. Such occurrences would result in additional CWT as well as a corresponding increase in maintenance workload associated with multiple repairs. While this is a limitation of the model, we do not believe that this limitation alters the results of the simulation in such a manner that will be significant. We have limited support for this belief in the fidelity shown by our "As Is" model against the real data.

As previously discussed, our model assumes continuous use of the PEIs. Even though MTBF is determined over time that captures both high and low operational tempos, failures will occur more often during periods of high usage. MTBF will be determined by the variable use of the weapon system, and will change as ranges in time periods are examined. Reliability of the system is thus directly related to operational tempo. Further refinement of the model using additional simulation software products could possibly demonstrate the results on A_o with sporadic patterns of PEI usage and resultant demand for repair parts, as well as multiple failures within a given month.

As previously stated, our goal did not consist of determining a proper or adequate stocking methodology for the SMU. Our use of historical demand data is one such methodology that we chose to demonstrate a possible stock posture. Applying other proven stocking methodologies based on other criteria could potentially refine the model.

As such, this is not necessarily a limitation since our model could be extended to consider optimal stock postures. But for the purposes of our study, we limited the determination of the relationship between CWT and A_o based on this stocking methodology alone.

Additionally, our model does not account for the non-unique nature of some NSNs. Numerous NSNs are applicable to multiple PEIs. Our stocking methodology for this study is based solely on the historical demand for repair parts for the AAV. Stocking for some NSNs at the SMU incorporates demand that results due to failures of these NSNs on other PEIs, at which point risk pooling of those NSNs will alter the total stock quantities. Therefore, our study does not incorporate the stock quantities that the SMU already stocks.

The value determined for CIVaR is based off of the ROP stock model and uses this value as the average inventory value during lead time (all of which must be acquired incrementally by the SMU to implement this policy). Since we have not tracked current allowance levels at the SMU (let alone determined the part of that allowance level which could be considered safety stock) we cannot estimate the incremental budgetary expenditure. Additionally, our model is only determining CIVaR for one end item, even though many of these NSNs are shared across multiple PEIs. The current stocking methodology for *every* PEI that the SMU supports would need to be considered before true incremental budgetary impact could be estimated. Hence, we believe that our limited 'upper bound' or 'maximum' budgetary impact CIVaR analysis is sufficient for the purposes and limited scope of this thesis.

Ultimately, our model is limited in that it provides results based on the inputs that we have available. Human error in data input into supply and maintenance systems affects abilities to use historical data for a picture of actual occurrences. During our research, we used the most relevant and accurate data that we obtained to ensure the most precise representation of our "As Is" and "To Be" simulations. With additional data demonstrating the distribution and variability of MTTR, ADT, and MTBF, the model could be updated to demonstrate the effects to A_o across the entire maintenance and supply spectrum. Nonetheless, our research using available data indicates that there is a quantifiable and demonstrable relationship between CWT and A_o. Yet, as we have

learned throughout our research, “a model should not be considered an adequate substitute for good judgment” (Phillips et al., 1987, p. 370).

VI. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS FOR FURTHER STUDY

This chapter presents the conclusion of our project, recommendations, and areas which should be considered for further research. In this study, we sought to demonstrate the intuitive nature between decreasing CWT and the resultant increase in A_o, as well as how improvements in A_o inevitably come at a cost. In the fiscally constrained environment we are inevitably facing in the future it is imperative to have a tool such as this model to show how significant the impact material stock decisions have on equipment availability. As we exhibit in the analysis of our research, that cost of material stock decisions will vary depending on the methods used to stock material with long lead times and the desired end state.

Through the conduct of simulations with various CWT and service level parameters, this study has ultimately presented evidence to substantiate that there is a quantifiable relationship between CWT and A_o, albeit a non-linear one. The nature of these two variables must be evaluated against the costs of achieving a desired A_o because the benefit is not always worth the investment needed to achieve it. The value of the relationship can only be determined by the decision makers' desired end state, whether in such terms as a desired A_o, higher probability of required FMC systems, or a certain level of risk reduction, all coupled with budgetary constraints.

A. SUMMARY

To identify the relationship between CWT and A_o, we determined that we had to model that relationship from the most basic perspective. To do this, we examined one type of PEI (the AAV) within one supported region (I MEF). This was a different approach than other studies in the past that aimed to quantify the relationship between A_o and CWT, which were focused on how the aggregate of all parts pertained to the aggregate of all equipment in DoD. At its root, the model we created in this project is a computer simulation using the Monte Carlo method to show the probabilistic impact that changes in CWT have on A_o. To accomplish this task, we took the A_o equation and

dissected it into its associated components. Based on historical data of the reliability of the AAV, MTTR, ADT, and CWT, our model provides probability distributions of A_o to aid decision makers in understanding the likelihood of outcomes. Since the variables that make up A_o are not deterministic in nature, it was essential that we study the behavior of these variables and assign stochastic values. This added touch of realism ultimately allowed us to model the past in a manner where the output of the model was nearly identical to the historical data. To arrive at some future end state, the model allows us to modify the conditions that affect CWT in order to determine the resultant changes in the distributional outcome of A_o.

This model uses the ROP stock method to set SMU stock quantities at a point where fill rates are aligned with user configured service levels, and measure the changes in A_o as material with unacceptable CWT thresholds are targeted for forward positioning at the SMU. In addition to its adjustability, the model measures the budgetary impact such stock methods pose to the MEF through a measure we have coined CIVaR, which measures the likelihood that a part is stocked and not used during the budget cycle. For the conduct of our simulation, we ran the model for 100,000 simulations at each possible combination of service levels of 0.8, 0.9, 0.95, 0.99 and CWT thresholds of 30, 20, 15, and 10 days. By demonstrating the differences in A_o under current conditions compared to A_o under alternative conditions of CWT thresholds and service levels, our model demonstrates the level of significance that reducing CWT has on improvements to A_o. Our study revealed that, when using various inputs, the associated outputs can be recorded to allow decision makers to base the service level and CWT threshold on desired A_o end states, given budgetary constraints.

B. RECOMMENDATIONS FOR FURTHER STUDY

1. Impact of Additional Variables on A_o

While this analysis may provide a foundation for quantifying a relationship between CWT and A_o, it is limited in its ability to demonstrate the entire effect on of all variables that impact total asset availability. This study primarily focused its analysis on supply-based issues and possible adaptions in supply policy that would reveal the

quantitative effects in monetary and readiness terms. While we have demonstrated a non-linear relationship between CWT and A_o, this study is incomplete in providing an understanding of how other variables have a role in impacting A_o. CWT analysis alone will reveal some of the measures that can be taken to improve readiness; however, to come to a holistic approach to improving A_o, further statistical analysis is necessary to show the degree to which other variables also impact A_o (MTBF, MTTR, ADT).

Such analysis must center on specific improvements to these variables. Improving the maintenance process itself, whether through lean initiatives, improved personnel management, or improved training, could reveal a decrease in MTTR and ADT, both on within the maintenance and supply communities. Additionally, since MTBF of an asset relies on the engineering aspects of an asset, analysis conducted on improvements to the initial acquisition or engineering aspects of equipment could result in higher levels of readiness. As with this study, a cost-benefit analysis would be necessary to determine if the received benefit of improved A_o is worth the costs.

2. Maintenance Capacity

Reducing CWT will deliver critical repair parts to the customer, the maintenance personnel, at a faster pace; however, this does not inevitably equate to the maintenance personnel having the ability to keep pace with improved arrival times of the parts. Further analysis is necessary to determine the sufficiency of maintenance capacity in personnel and equipment.

3. Distinct MTTR

Our model used the exponential distribution for time to repair. In reality, each NSN has its own MTTR with its own distribution. Further analysis is necessary to assign a time to repair distribution for each NSN. The associated time to repair distribution for each NSN could be incorporated into a final model that would demonstrate the complete repair cycle with more fidelity.

4. Wholesale Level Stocking Methodology

A secondary approach to this study would be to address the modification of stocking methodology at the NICPs at the wholesale level that would decrease CWT for critical repair parts. As previously stated, DoD's goal for average CWT is 15 days. When examining the AAV data we used for our research, DLA's average CWT for critical repair parts was 26.24 days. If such wholesale entities as DLA desire to improve customer service, a study of their stocking criteria in relation to CWT should be further explored in order to demonstrate possible courses of action that can be taken at that level to reduce the burden on the services. Further, if the NICPs ensure they address their stocking methodology based on the ILC quadrant model discussed by McGowan (2002), and couple it with improved service levels, average CWT for critical repair parts at the wholesale level should witness a reduction that will result in benefits to A_o.

5. Repair Part Reliability

Our study is centered on affecting the impact of CWT for repair parts. Demand for repair parts is driven by the rate at which each NSN experiences a failure. While supply professionals at the intermediate level can affect the stocking posture of NSNs, a further examination by DoD strategic supply professionals may be warranted to seek out the acquisition of more reliable repair parts. A study of the comparison between investment in pre-positioning repair parts and investment in more reliable repair parts may demonstrate the most cost effective method for improving A_o.

6. Re-posturing of Forces in the Pacific

As U.S. forces begin to focus on the Pacific Area of Operations, an increased presence in Australia will require investment to ensure a sufficient readiness posture. The Australian quarantine process takes up to 3 months for all incoming cargo. Simply relying on a robust distribution network to bring critical repair parts to forces operating in Australia is clearly inadequate. Pre-positioning the requisite amount and type of repair parts will be critical to the success of these forces. Due to the Australian quarantine, additional time must be considered when calculating lead time. Our model can assist in determining the impact of such investment; however, further analysis is required to

determine the unique situation of deploying to Australia and the stocking of additional parts that factor in the additional lead time due to the quarantine.

C. CONCLUSIONS

As we approach the age of reduced budgets, the notion of decreasing inventory, especially excess, becomes even more pertinent. Replacing inventory with information has become an axiom in logistical arenas, but supply professionals must continue to seek intelligent ways to maintain higher levels of readiness while reducing inventory costs. This study lays out the first part of this charge, but at significant upfront costs. Supply chain analysis must include establishing stronger partnerships between intermediate and wholesale supply activities to improve information sharing. In so doing, the very goal of each activity of providing logistical support for equipment readiness will become aligned. The resultant effects will be higher readiness at lower costs.

As intermediate supply activities seek to stock the right repair parts in the right quantities based on high levels of demand, they will ensure higher fill rates for high turnover items. To replace these highly demanded items, intermediate supply activities provide high demand to the wholesale level. Variability in demand must be considered whether based on seasonality, operational tempo, or some other identifiable factor. Without proper communication, both the intermediate and wholesale levels may stock unnecessarily high amounts of these items. Consequently, commercial vendors who supply the wholesale supply chain also maintain high levels of these items.

With proper communication between the intermediate and wholesale level, the amount of inventory stocked at the intermediate level for these high demand items could potentially be reduced. The same can be said for the relationship between the wholesale and commercial vendor levels. Such information sharing will reduce the need for upfront investments for stocking items that have acceptable CWT from the next echelon in the supply chain, resulting in fiscal resources that can be used for items with longer CWT or higher uncertainty based on the variability in demand. Therefore, the DoD cannot only look at the high demand of critical repair parts in stock determination, but must identify those critical assets with long and varying CWT. As the relationship between criticality

and CWT is applied, investment in those items can be evaluated using a model such as ours to determine the effect on readiness.

With an understanding that all PEIs and NSNs are not equally important, as McGowan (2002) discussed in his article, we can identify that both the intermediate and wholesale levels of supply are not addressing the impact that CWT has on A_o. This is happening because, without models like this one, there is no clear understanding of the relationship between these variables. Our model reveals that arbitrarily assigning service levels to tackle the problem will not always produce desired results, and that the gains to A_o are rendered irrelevant at certain points due to the high investment of achieving those service levels. This study is quantifiable proof that reducing customer wait time will improve readiness and readiness risk when the focus of material stock decisions is placed on critical repair parts.

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